Modelling Mosquito Prevalence on a City-Scale in Gothenburg, Sweden

A Methodological Development Study

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Abstract

Mosquitoes are one of the most prominent carriers (or vectors) of diseases worldwide, which has an impact on human societies, as up to 1 million people pass away each year from mosquito-related diseases. Mosquitoes are known carriers of, e.g., malaria, dengue fever and West Nile virus. These pathogens or viruses are temperature dependent, and a warmer future climate is believed to increase their geographical spread. Future warming may also lead to invasive species of mosquitoes establishing in new areas. One of the most common species of mosquitoes in urban areas in Europe is the *Culex pipiens.* The *Cx. pipiens* is a known carrier of different viruses and pathogens, e.g., the West Nile virus, and thus, several campaigns to control the species have been organized in cities all over Europe. Detailed species distribution models of mosquitoes could improve such surveillance- and mitigation campaigns.

By utilizing Multi-Criteria Analyses, the aim of this study was to model suitability of egg-laying (or oviposition) sites and adult distribution of the *Cx. pipiens* in the city of Gothenburg. Species distribution models of mosquitoes have not been previously performed on a city-scale. The results indicate large intra-urban variations in suitability for both oviposition and adult distribution. The results from the oviposition-model indicate highest suitability in, e.g., cemeteries and residential gardens. Regarding adult distribution, highest suitability is found in densely vegetated areas. An exposure analysis was also performed, which indicates that human exposure to *Cx. pipiens* is generally low in Gothenburg. However, human exposure to *Cx. pipiens* in Gothenburg may increase as studies have found that a warming climate might lead to changed dynamics in mosquito-human interactions. The study concludes that modelling mosquito suitability on a city-scale is possible, but further research is needed to validate and develop the models.

Key words: *Culex pipiens, Weighted Multi-Criteria Analysis, mosquito suitability, Species Distribution Model, city-scale*

Acknowledgments

The presented thesis marks the end of a five year long academic journey. I started the journey in 2016, nervous, confused, and excited for the future. The journey ends now, in 2021, with me being less nervous, less confused, but with a maintained excitement for what is to come.

The process of writing this thesis has been interesting, challenging, and at times frustrating. At times I was filled with excitement, like when the model simulations produced believable results. Other times, I wanted to bang my head against the desk, for example when an algorithm did not work for the nth time. In these times of doubt and despair, I was fortunate enough to be surrounded by smart and supportive people.

I am deeply grateful towards my supervisors, Associate Professor Fredrik Lindberg, and Professor Sofia Thorsson. Fredrik's guidance and assistance, especially regarding GIS-related questions, were essential for a successful thesis-work. Sofia's expertise regarding the scientific work-process and her many words of encouragement has significantly improved the quality of the report. Further, I would like to thank Professor Georgia Destouni for tips on how to improve the models.

I also want to express my warmest gratitude to PhD Anders Lindström, for sharing his extensive knowledge about mosquitoes and his support in finding relevant articles for me to study further. Without the assistance from PhD Anders Lindström, this study would have been hard to conduct.

My fellow Geography students also deserve a huge thank you, for going on this journey with me. Thank you for proof-reading, emotional, and work-related support, and the many coffee breaks.

Last but certainly not least, I want to thank my loved ones for their eternal support and confidence-inducing words.

Ville Stålnacke

Göteborg, 2021-05-25

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1. Introduction

1.1 Background

Mosquitoes (*Diptera: Culicidae*) is the common name for a group of circa 3500 species of small flies. Due to this high variety in species, mosquitoes are spread all over the world, and have a major impact on human societies. In some parts of the world, the mosquito is only considered a nuisance, due to the itchy rash caused by their bites. In other parts, the mosquito is considered a threat to human lives, as up to 1 million people pass away every year from mosquito-borne diseases (Caraballo & King, 2014; Center for Disease Control and Prevention, 2019) This high morbidity and mortality is caused by mosquitoes being the most notable **vectors**, or carriers, of diseases like malaria, dengue fever and West Nile virus, among others (Juliano & Philip Lounibos, 2005; Medeiros-Sousa, Fernandes, Ceretti-Junior, Wilke, & Marrelli, 2017). These diseases are most prominent in tropical and subtropical regions, but outbreaks of different diseases have occurred in more temperate areas as well.

Air temperature is the major factor influencing the possibility for pathogens or viruses, to develop in mosquitoes. In general, pathogens cannot develop when the air temperature gets too cold (European Centre for Disease Prevention and Control, 2020). However, with a changing climate, exotic and disease-carrying species of mosquitoes may spread to areas of higher latitude and/or altitude, with potential health hazards as a consequence. For instance, a study from Serbia modelled the possible future extent of the Asian Tiger Mosquito (*Aedes albopictus)*, an invasive species which can be a potent vector for several viruses (Petrić, Lalić, Ducheyne, Djurdjević, & Petrić, 2017). The study found that the entire country of Serbia would be more suitable for the *Aedes albopictus* by the end of the 21st century, due to increased annual and seasonal air temperatures.

To gain knowledge about the spread of mosquitoes and pathogens, it is of importance to model the possible future extent of different mosquito species. With a solid knowledge base, it might be possible to act proactively to lessen the future impacts of the spread of invasive mosquitoes and the pathogens they carry (Petrić et al., 2017). Species Distribution Modelling (SDM) is a well-known and widespread methodology to gain insight in the potential geographical extent of different species. SDM has successfully monitored the potential spatial distribution of e.g., owls (Bradsworth, White, Isaac, & Cooke, 2017), ticks (Rochlin, 2019) and giant pandas (Connor et al., 2019). There are common denominators for these studies, and SDM: s in general. Firstly, the spatial scale is large, ranging from regional to continental scale. Secondly, the input data into the models are often sampled data of species occurrences as well as environmental data of the sampling areas. The potential sites of distribution are sites that have suitable environmental characteristics but lack current inhabitants of the species.

The SDM-methodology described above provides relevant information of potential habitats on a large scale. However, it fails to provide information about the difference in distribution *within* the large-scale suitable areas. Small-scale differences of suitability within large-scale suitable areas can be significant and are caused by, e.g., difference in land use or land cover, and small-scale climatological variations. For example, a mosquito is more likely to be found in a densely vegetated area than in a highly urbanized area, even though the large-scale climatological conditions are suitable in both areas. The spatial resolution of small-scale SDM: s would allow for a more detailed overview of species distribution, meaning that risk assessments and surveillance measures could be more accurate and pinpointed.

To be able to model species prevalence on a smaller scale, several variables need to be included, where these variables are weighted against each other to locate areas that are suitable for the specific species. Such parameters, e.g., land use and land cover, in themselves might not be meant to be used for modelling species prevalence, but they can be indicators of suitability, i.e., they can be used as **proxy-data**. Small scale SDM: s using proxy-data has not been thoroughly researched and is therefore a subject that should be explored. The knowledge provided by small scale SDM: s regarding mosquito prevalence could potentially improve mosquito and disease-control campaigns, and thus alleviate the negative impact of mosquito presence.

1.2 Aim and research questions

The aim of this study is to develop models that simulate mosquito prevalence on a city-scale, in Gothenburg, Sweden. An exposure analysis of potential areas of interactions between humans and mosquitoes will also be performed. Furthermore, models utilizing nationally available data, meaning that the model can be implemented in other cities in Sweden, will be developed. The following research questions will be answered in the study:

- What characterizes the spatial patterns of modelled suitability for egg-laying sites, and adult distribution of *Culex pipiens* in Gothenburg?
- How does the modelled suitability for adult distribution change when altering model-parameter weights?
- What characterizes the spatial patterns of human exposure to *Culex pipiens* in Gothenburg?

2. Literature review of key themes

2.1 Culex pipiens

In Europe and Sweden, one of the most common species of mosquito is the *Culex pipiens,* also known as the **Northern House Mosquito**. The *Cx. pipiens* is an environmentally adaptable species, meaning that it can thrive in different milieus (Townroe & Callaghan, 2014), and is therefore well established in urban settings. The *Cx. pipiens* is a known pest in urban environments and several campaigns with the aim to control the species have been organized in many European cities (European Center for Disease Prevention and Control, 2020).

2.1.1 Environmental preferences of the *Cx. pipiens*

Cx. pipiens lay eggs on water surfaces in a variety of water containers, of both natural and artificial character. The process of laying eggs is known as **oviposition.** Known places for oviposition are puddles, storm sewers, ditches and buckets (Bowden, Magori, & Drake, 2011; European Center for Disease Prevention and Control, 2020). Due to the adaptability of the *Cx. pipiens,* they are experts at finding oviposition-sites in a variety of locations. However, they depend on water for oviposition, so they are more often found in urban settings where small water containers are left undisturbed, e.g., in residential gardens and cemeteries (Rydzanicz, 2021; Townroe & Callaghan, 2014). Such areas are often popular for urban gardening, an activity that requires water for irrigation. Therefore, it is more common to find still standing water in such locations, which makes these areas suitable for oviposition for *Cx. pipiens.* When a suitable site for oviposition is found, a single female mosquito can lay around 200 eggs on the water surface (European Center for Disease Prevention and Control, 2020). The development from egg to larvae is temperature dependent, with faster development at warmer air temperatures. In air temperatures of 30°C, the eggs hatch after one day, after three days at 20°C, ten days at 10°C, but below 7°C, the development cannot be completed. The development from larvae to adult is also dependent on the air temperature, as it takes 6-7 days at 30°C and 21-24 days at 15°C (ibid).

A study in England (Townroe & Callaghan, 2014) found that *Cx. pipiens* used rainwater collectors in gardens as oviposition sites, and that an increased usage of water containers in gardens have benefitted urban mosquitoes like the *Cx. pipiens*. Furthermore, the study found that the *Cx. pipiens* had a faster reproduction rate in containers placed in an urban setting, relative to containers placed in a rural setting. One explanation for this was that the urban area was relatively warmer than the rural area, due to the Urban Heat Island-effect (UHI), leading to faster development rates. The article found that a drought period, where irrigation via hoses was prohibited, caused an increase in the sales of rainwater collectors. Moreover, Townroe & Callaghan, (2014) states that an increased insecurity regarding rainfall patterns might prompt more people to purchase rainwater collectors. This fact, coupled with a warming climate may lead to more oviposition sites and faster reproduction rates for *Cx. pipiens* in some parts of England.

Cemeteries are another urban setting that is found to be suitable as an oviposition site for the *Cx. pipiens* (European Centre for Disease Prevention and Control, 2020; Rydzanicz, 2021). Cemeteries are suitable for the *Cx. pipiens* due to a high availability of all of their preferred resources, like food (commonly birds), shelter, and water (Vezzani, 2007). Cemeteries generally have high vegetative cover, and there are usually a large number of artificial water containers in cemeteries, like vases, buckets, and rainwater collectors for irrigation (Rydzanicz, 2021; Vezzani, 2007). In a study in Wroclaw, Poland, the authors studied the suitability of water supply wells in cemeteries for mosquito larvae development (Rydzanicz, 2021). The study identified all mosquito species found in the cemeteries. They found that the *Cx. pipiens* constituted 95% of all present mosquito species in the water supply wells. Furthermore, they found that the larval development peaked in June, when the average air temperature was around 22°C. The study concluded that cemeteries provide a suitable and important breeding ground for native mosquito species in Poland, especially for the *Cx. pipiens.*

Another urban setting that is suitable as an oviposition site for the *Cx. pipiens* is allotment gardens, but allotments have not been researched in the same capacity as cemeteries and residential gardens. However, similar traits are found in allotments as in cemeteries and residential gardens, a less organized area with a higher likelihood of gardening and therefore a higher number of water collectors and containers. A study of the invasive *Aedes japonicus japonicus* in the Netherlands (Ibañez-Justicia et al., 2018) found that allotment gardens are highly suitable as breeding sites for the species, due to a high number of artificial water containers, e.g., rainwater collectors. The study from Wroclaw, Poland (Rydzanicz, 2021) states that the *Aedes japonicus japonicus* and the *Cx. pipiens* have similar preferences regarding sites for oviposition. Therefore, there is a high probability that allotment gardens have a high suitability as oviposition site for the *Cx. pipiens.*

The *Cx. pipiens* is also known to use naturally created water gatherings, like pools, swamps, and ponds, for oviposition, but they are not as prominent in such areas. Artificial water containers are preferred over natural water bodies due to the artificial containers being smaller than natural water bodies, meaning there is less competition with other species (Vezzani, 2007). This lack of competition means that the *Cx. pipiens* can grow fast in numbers, and they do not have to worry about predation from other species (ibid).

When the *Cx. pipiens* has developed from larvae to adult mosquito, their main goal is to find shelter and bloodmeals, in the form of birds. The adult *Cx. pipiens* is mostly found in highly vegetated areas in the urban environment, as the vegetation provides them with many resources they seek; humidity, shade, wind reduction, and shelter (Vezzani, 2007). Furthermore, the *Cx. pipiens* is ornithophilic, meaning it is a bird expert and looks for birds as their primary bloodmeal. Birds are more commonly found in vegetated areas (Hedblom & Söderström, 2010; Verdonschot & Besse-Lototskaya, 2014), so the *Cx. pipiens* find bloodmeals in the vegetated areas as well. Sampling studies of *Cx. pipiens* have found that they are more often captured at canopy height, than ground height (Swanson & Adler, 2010) This is explained by their ornithophilic nature, as birds are more often found at canopy heights. The *Cx. pipiens* is limited in their geographical distribution after birth, as they seldom fly further than 500 meters from the birthplace (European Centre for Disease Prevention and Control, 2020; Verdonschot & Besse-Lototskaya, 2014). However, as they are miniscule in size, the *Cx. pipiens* will be transported further by strong winds. So, there is a possibility for them to travel further than 500 meters, but not by their own capacity (Verdonschot & Besse-Lototskaya, 2014).

To conclude the information above, regarding oviposition sites the *Cx. pipiens* prefer less organized urban settings with a high number of artificial water containers (e.g., cemeteries, residential gardens, and allotment gardens). Furthermore, their development from egg to adult is accelerated with increased air temperature.

Regarding their adult stage, the *Cx. pipiens* is likely to be found in vegetated areas (which provide shade, humidity, shelter, wind reduction and a higher likelihood of bloodmeals in the form of birds). Moreover, the adult *Cx. pipiens* are more likely to be found in areas close to their birthplace, as they seldom fly further than 500 meters.

2.1.2 Cx. pipiens and West Nile Virus

The *Cx. pipiens* is a vector for several viruses or pathogens, e.g., West Nile virus, Usutu virus, and Rift valley Fever Virus, among others. Although all viruses have severe consequences, the focus in this part will be on the West Nile virus, as Europe has experienced a higher spread of the virus in recent years (Burki, 2018).

The *West Nile Virus* (WNV) is a virus whose infection mostly causes mild symptoms like nausea, headache and fever, but the infection can be deadly (Public Health Agency of Sweden, 2019). Due to its ornithophilic character, the role of *Cx. pipiens* in the spreading of WNV is as a spreader of WNV between birds, and not as a spreader of WNV to humans (European Centre for Disease Prevention and Control, 2020). Very rarely do the *Cx. pipiens* bite humans. However, an increased spread of WNV between birds may spill over to humans when other mosquito species are present. Other species that are more likely to feed on both birds and mammals can spread the WNV-pathogen from an infected bird to a human (ibid). Several studies have found that the number, and density, of *Cx. pipiens* must be high for successful transmission of the WNV pathogen to humans (ibid). The human impact of WNV, compared to other diseases like malaria and yellow fever, are not as severe. This is caused by humans being so called dead-end hosts for WNV, meaning that the virus is not amplified in human hosts, which limits the potential spread of WNV among humans (Burki, 2018).

Although the disease-symptoms of WNV usually are mild, and the spread among humans is low, the disease is serious and can be deadly. In 2018, there was an outbreak of WNV in the continental Europe, with circa 2000 infected, of which 180 died (Burki, 2018). The reported cases and deaths were predominantly in Southern and Central Europe, e.g., in Greece, Croatia and Romania (European Centre for Disease Prevention and Control, 2018). The transmission season of 2018 saw a substantially higher number of WNV infections than previous seasons. The total number of cases in 2018 was 2083, while the total number of cases for the *seven* previous years was 1832 (ibid). The spike in cases is believed to be caused by the hot summer, as mosquitoes breed and develop faster in warmer weather conditions (Burki, 2018). Therefore, as the climate is warming, there is a high risk of increased severity in the annual outbreaks of WNV in Europe. These warming trends may also lead to other mosquito species, as well as other viruses and pathogens being able to establish themselves in higher latitude and/or altitude areas (Becker, 2008; Petrić et al., 2017).

2.2 Urban climate

2.2.1 Air temperature in urban areas

Cities affect their own climate, both on larger and smaller scales. These climatological alterations are caused by a modification of the landscape, as natural environments like forests or grasslands are turned into, e.g., parking lots or residential areas. Due to the impervious characteristics and high heat holding capacity of urban materials (like concrete and asphalt), metropolitan areas are often warmer than their rural surroundings, especially during nighttime, a phenomenon known as the Urban Heat Island (UHI) (Oke, Mills, Christen, & Voogt, 2017). Within an urban environment, there are microclimatological variations, due to differences in land use, urban form, and structure, all of which affect the intensity of the UHI-phenomenon. Generally, if temporal and meteorological effects are not considered, the strongest UHI-effect is found over densely built-up areas, characterized by tall buildings and narrow streets (Oke, 2002). One measure of density in a city is the Height to Width-ratio (H/W-ratio), which is a value derived from the height of a building relative to the width of the street where the building stands, where higher H/W-ratio values indicate higher density. The H/W-ratio has been found to correlate well with the maximum UHI-effect, as a higher density (or H/W-ratio) leads to higher radiation trapping, lower wind speeds and higher anthropogenic heat release, all of which lead to a warmer microclimate (Bakarman & Chang, 2015). Moreover, an increase in density often means removing cooling agents such as vegetation or water, replacing them with tall buildings made of high heat holding materials like concrete. Oke (2002) found the relationship between H/W-ratio and maximum heat island intensity (under prime conditions) to be (equation 1):

$$\Delta T_{u\text{-}r(max)} = 7.54 + 3.97 \ln(H/W) \qquad (1)$$

where $\Delta T_{u\text{-}r(max)}$ is the maximum heat island intensity and ln(H/W) is the natural logarithm of the H/W-value.

The UHI-effect is strongest in densely built areas, and it is weaker in less dense areas, vegetated areas, or areas with water. Parks, lakes, and open areas all have a cooling effect. Air temperatures have been found to decrease by as much as 3-4° K in city parks during mid-day in the summer (Shashua-Bar, Pearlmutter, & Erell, 2009). However, the cooling effect of vegetation is a complicated matter, which is affected by the type of vegetation, the irrigation regime, and the form of the adjacent cityscape (ibid). In a review article about heat reduction strategies in cities by (Krayenhoff et al., 2021) the authors reviewed 146 studies concerning numerical models of urban air temperature reduction. Among other findings, they introduced a vegetation cooling metric, the Vegetation Cooling Effectiveness (VCE). The VCE indicate that trees provide ~0.3 °C cooling for every 0.10 increase in canopy cover, for afternoon clear-sky summer conditions.

2.2.2 Wind in urban areas

Wind in urban areas is highly chaotic and is influenced by different driving forces on different scales (Oke et al., 2017). The large-scale wind direction and speed is driven by pressure differences high up in the atmosphere and is not of interest for this study. On smaller scales, the wind in urban areas is affected by the surface elements, form, and structure of the city (ibid). Buildings and vegetation influence wind patterns at street level. In general, a higher degree of buildings and vegetation relative to the wind direction means a higher aerodynamic resistance for the urban surface, and wind speeds are decreased. (Wong & Nichol, 2013).

2.3 Species Distribution Models (SDM)

With increased evidence of the negative anthropological impact on ecosystems worldwide there is an increasing interest in biodiversity research and preservation, in many parts of the world (van Proosdij, Sosef, Wieringa, & Raes, 2016). Despite this, knowledge of species distribution is insufficient in large areas, especially over areas which are difficult to access. The development of Species Distribution Models (SDM: s) have given researchers a powerful tool to work around a lack of sampling data (ibid). SDM: s are numerical models that use species sample data and environmental parameters to predict occurrence or abundance of species distribution in a predetermined area (Elith & Leathwick, 2009). The output of an SDM shows areas with environmental suitability for the species to establish. This output can be used to fill the gaps in the knowledge of geographical extent of the studied species, as field sampling can be both time consuming and difficult to perform (Linder et al., 2012). The advances in computational power and mathematical modelling have led to SDM: s seeing a rise in popularity. Their increased usage has led to improvements in many ecological fields, like conservation studies, studies of invasive species and habitat protection measures (Bradsworth et al., 2017). Figure 1 shows a simplified figure of the principal components of an SDM. The rainfall zone-suitability and altitude zone-suitability is checked in all areas of current observations. The habitat models find areas with suitable living conditions but lack sampling data.

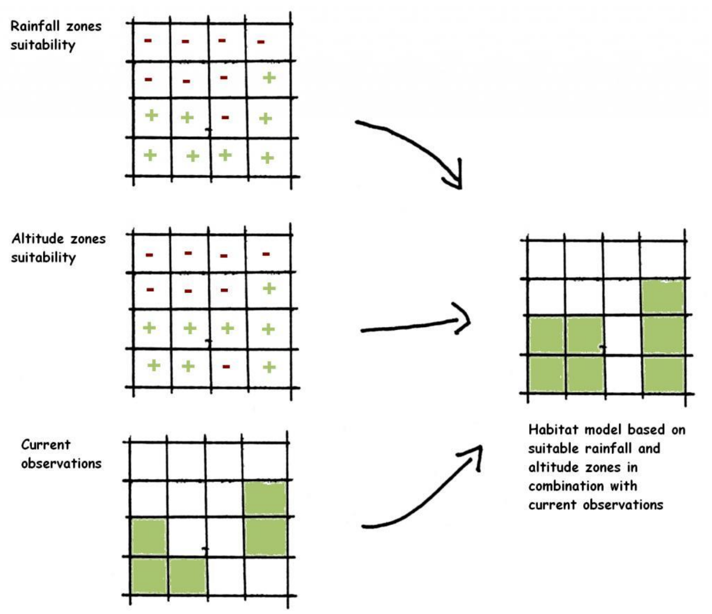

Figure 1. A simplified figure of the principal components of an SDM. Suitable areas are found where the rainfall zones suitability and altitude zones suitability overlap, and where sample data is lacking. Image courtesy of (Wikimedia n. d.) under the Creative Commons License.

SDM: s have been used in numerous studies. In a study over North America (Rochlin, 2019), the authors modelled suitable areas for the Asian Longhorned Tick (*Haemaphysalis longicornis* Neumann, Acari: Ixodidae). The tick is native to East Asia and Oceania and had recently been detected in areas in North America. They used sample data and environmental variables e.g., annual mean air temperature, maximum air temperature of warmest month and annual precipitation to model areas with high suitability of the tick in North America. Rochlin (ibid) found suitable habitats in most of the coastline of eastern North America, as well as in other areas. They argue that this is of concern, as the Asian Longhorned Tick is a vector for diseases. The knowledge from their study can help with preventive measures, e.g., inform the public and prepare public health agencies for the potential risks of the tick.

A study from western Sweden (Stighäll, Roberge, Andersson, & Angelstam, 2011) used an SDM to look at the potential habitats for White-backed woodpeckers (*Dendrocopos leucotos* Bechstein). They used sample data, traditional remote sensing data about tree species composition and forest age, as well as biophysical proxy variables for the forest stands. Some examples of biophysical proxy variables were slope of the forest stand, distance to roads and distance to water. Their results showed that biophysical proxies can be utilized together with traditional forest data to better model habitat suitability of the White-backed woodpecker. They concluded that biophysical proxy variables are especially useful if a species depend on natural properties that are not directly identifiable via traditional forest data (ibid).

SDM: s rely on sample data of species occurrence and abundance as one parameter in the modelling. However, if species sampling data is lacking, a traditional SDM becomes challenging to perform. Instead, other methodologies to perform habitat modelling must be considered. One such methodology is *Weighted Multi Criteria Analyses* (WMCA).

2.4 Weighted Multi Criteria Analyses (WMCA)

WMCA: s are routinely utilized in urban planning, for example to find the most suitable site for a new establishment, be it a school, shop or any other establishment. A WMCA is a well suited tool for such an application, as the goal is to find the most suitable location from a selection of criteria (Rikalovic, Cosic, & Lazarevic, 2014). WMCA: s and GIS is a powerful combination, and has been widely utilized for solving spatial issues in urban planning (J. Chen, 2014). In a WMCA, different criteria are chosen, their original values are given new values depending on their suitability (on the same scale, often 1-10) and the criteria are then weighted against each other to find the most suitable location from the given criteria.

2.5 Sensitivity Analysis

Sensitivity analyses has a crucial role in validation of numerical models, as the robustness of the outcome of a model can be checked against small alterations in the input data, to identify and evaluate the influence of individual parameters (Chen, Yu, Shahbaz, & Xevi, 2009). The reliability of a model is greater after having run a sensitivity analysis (ibid). When applying sensitivity analyses on a WMCA, the commonly used approach is to change the values and weights of each criteria, one at a time, to understand how the model acts and why (ibid).

3. Study area

To test the possibilities of using proxy-data to model mosquito prevalence on a city scale, the high latitude (57.70°N, 11.97°E) city of Gothenburg is chosen as study area. Gothenburg is the second largest city in Sweden, with about 583 000 inhabitants as of the end of 2020 (City of Gothenburg, n. d.). The city consists of different urban land structures, from densely built-up areas in the central part, to woodlands and open fields at the outskirts of the city center (figure 2). The climate of Gothenburg is influenced by the proximity to the ocean which affects both the air temperature and the precipitation. The summer temperatures are relatively cool for the latitude (16.3° C in average air temperature in June to August, 1960-1990) (Thorsson et al., 2017). The winters are relatively mild, due to the warming influence of the Gulf Stream (-0.4° C in average air temperature for December to February, 1960-1990) (ibid). The annual precipitation of Gothenburg is about 800 mm, and is distributed uniformly over the year, with circa 200 mm in both the summer months (June to August) and the winter months (December to February) (Rana, Madan, & Bengtsson, 2014). The main wind direction of Gothenburg is from the sea, i.e., from the west.

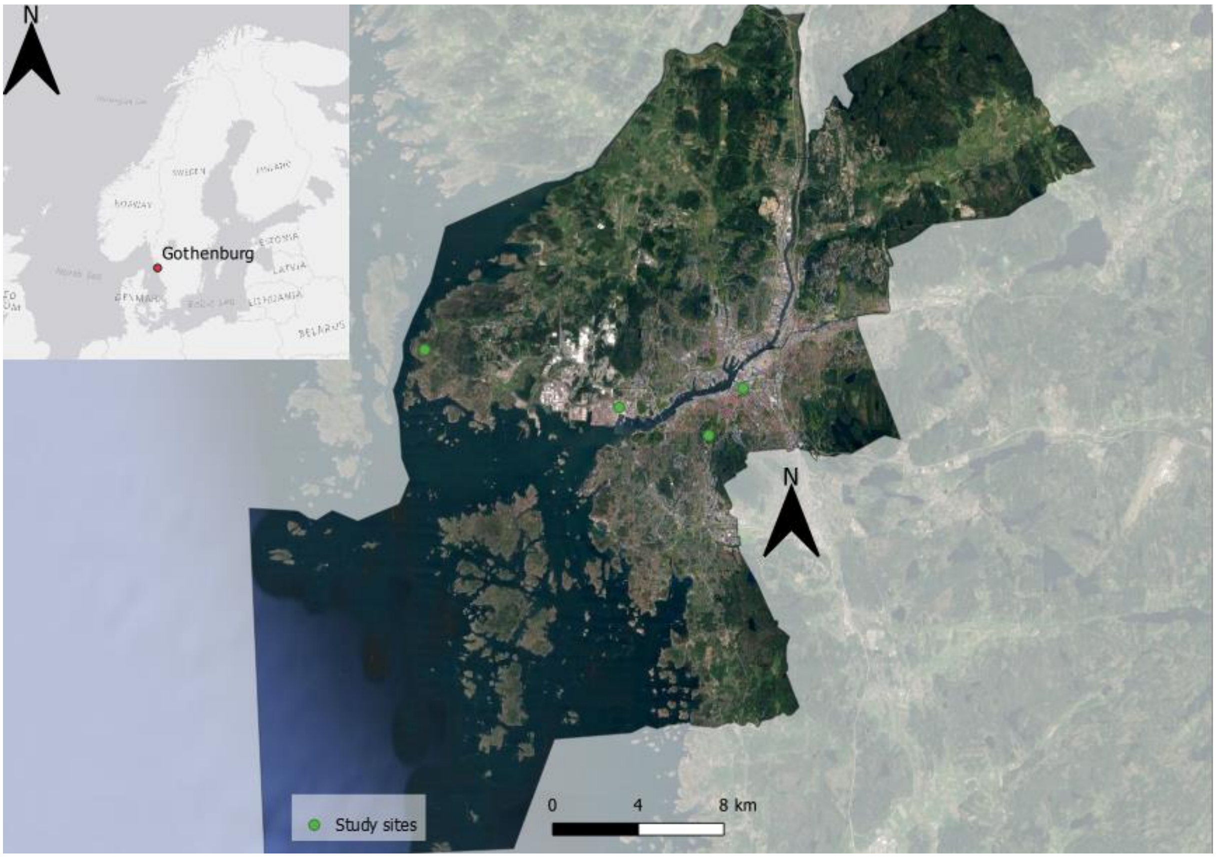

Figure 2. A map showing the study area. The map shows a satellite image of the city of Gothenburg, the city's location in Sweden, and the location of the smaller scale study sites within the city.

3.1 Culex pipiens in Gothenburg

There are a variety of different mosquito species present in Gothenburg, one of the more common species is the *Cx. pipiens*. The life cycle of the *Cx. pipiens* is influenced by the climatological characteristics of an area. A study from Southern England by Ewing, Purse, Cobbold, Schäfer, & White (2019) found the active season for the *Cx. pipiens* to be from spring (April - May) until the fall (August - September) due to the air temperature being too low for egg and larvae to survive in the other months (ibid; European Centre for Disease Prevention and Control, 2020). Similar seasonal dynamics are likely found in Gothenburg, as Southern England has a similar climate to Gothenburg. In the fall, when air temperatures decrease, the adult *Cx. pipiens* enter a diapausing state, while they wait for the warmer temperatures of the spring months (European Centre for Disease Prevention and Control, 2020). As mentioned previously, the *Cx. pipiens* is a known carrier of the West Nile Virus (ibid). Fortunately, the climate of Gothenburg is currently too cold for the West Nile virus-pathogen to develop, so the disease has not had any outbreaks in Northern Europe (Public Health Agency of Sweden, 2019). But with a warming climate, the pathogen will likely spread to more high latitude areas (Petrić et al., 2017), like Gothenburg.

4. Data and methodology

In this chapter, the data and the methodology used in the study will be described. The data used in the study was mainly raster data with a pixel size <= 10 meters. Some vector datasets were utilized to complement the raster data. A more detailed explanation of the input-data will be provided below (section 4.1). The methodology is split into two main parts, Graphical Modeler (section 4.2.1) and WMCA (section 4.2.2) due to the utilized WMCA-plugin lacking a Graphical Modeler implementation. A simplified workflow of the modelling process can be seen in figure 3. In general, the models built in QGIS Graphical Modeler were used to prepare, manage, and reclassify the datasets that were used as inputs in the WMCA-plugin. The WMCA-plugin was then used to derive maps over mosquito suitability, both regarding oviposition sites and adult distribution maps. The adult distribution map, from the adult WMCA, was used to perform a sensitivity analysis (described in section 4.2.3) as well as an analysis regarding human exposure to mosquitoes (described in section 4.2.4).

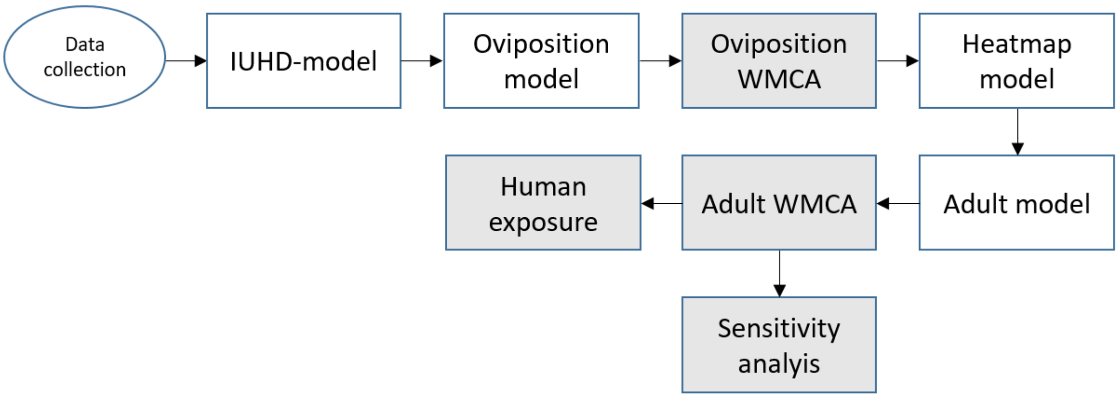

Figure 3. A simplified version of the workflow utilized in the study. White boxes indicate models built in the Graphical Modeler. Grey boxes indicate study results, which are shown in the results (chapter 5). These steps are further described in the methodology (section 4.2).

The data used in the study, as well as the suitability of the parameters for the models were based on scientific articles describing the preferences of the *Cx. pipiens*, as well as on expert knowledge provided by PhD Anders Lindström, researcher at the National Veterinary Institute of Sweden.

4.1 Data

The datasets used for the study are presented in table 1. The ambition of the data collection was to find data with a national coverage, as one aim is for the models to be able to be implemented in other cities in Sweden.

Three datasets were used for fine scale building-, ground- and vegetation heights, namely a Digital Surface Model (DSM), a Digital Elevation Model (DEM) and a Canopy Digital Surface Model (CDSM), all produced at the Department of Earth Sciences at the University of Gothenburg. The datasets are derived from LiDAR-data produced by the Planning and Building Authority at the City of Gothenburg. The LiDAR-data was retrieved in October 2010, at a flight altitude of 550 m. It had an average pulse density of 13.65 m^{-2} and a footprint diameter of 0.13 m. The Leaf Area Index (LAI)-dataset is also derived from the same LiDAR-data, see Klingberg, Konarska, Lindberg, Johansson, & Thorsson (2017) for information about the LAI-production. These datasets do not have national coverage. However, there is national coverage of LiDAR-data, so it is possible to produce similar datasets for other parts of Sweden.

The national land cover datasets from the Swedish Environmental Protection Agency were used for high resolution raster data of land cover, land use and object heights. In Swedish, the datasets are called *Nationella Marktäckesdatan,* (acronym NMD). The mapping for the NMD-data was performed between 2017-2019, and the plan is to update the mapping every five years (Swedish Environmental Protection Agency, 2020).

Two vector datasets were used, one building dataset and one land use dataset, to locate buildings and other land uses of relevance. Both were collected from the Swedish Mapping Cadastral and Land Registration Authority (2021).

Table 1. A table showing the datatype, pixel size, supplier, coverage, and model of use of the datasets utilized in the study.

Data	Datatype	Pixel size (m)	Supplier	Coverage	Model of use
Digital surface model (DSM)	Raster	1	Institution of Earth Sciences, University of Gothenburg	Gothenburg	Intra Urban Heat Difference, Oviposition
Digital Elevation Model (DEM)	Raster	1	Institution of Earth Sciences, University of Gothenburg	Gothenburg	Intra Urban Heat Difference, Adult

Canopy Digital Surface Model (CDSM)	Raster	1	Institution of Earth Sciences, University of Gothenburg	Gothenburg	Intra Urban Heat Difference
NMD Land Cover	Raster	10	Swedish Environmental Protection Agency (Naturvårdsverket)	National	Oviposition, Adult
NMD Land Use	Raster	10	Swedish Environmental Protection Agency (Naturvårdsverket)	National	Oviposition
NMD Object Heights 0.5-5 meter	Raster	10	Swedish Environmental Protection Agency (Naturvårdsverket)	National	Adult
NMD Object Heights 5-45 meter	Raster	10	Swedish Environmental Protection Agency (Naturvårdsverket)	National	Adult
Buildings	Vector	-	Swedish Mapping, Cadastral and Land Registration Authority (Lantmäteriet)	National	Oviposition
Land Use Vector	Vector	-	Swedish Mapping, Cadastral and Land Registration Authority (Lantmäteriet)	National	Oviposition, Adult
Leaf Area Index (LAI)	Raster	1	Institution of Earth Sciences, University of Gothenburg	Gothenburg	Adult

4.2 Methodology

4.2.1 Graphical Modeler

Four models were created in the Graphical Modeler in QGIS, the Intra Urban Heat Difference model, the Oviposition model, the Heatmap model and the Adult model. The role and process of each model will be presented below in individual subsections.

4.2.1.1 Intra Urban Heat Difference (IUHD) model

To identify the variations in air temperature within the city, an Intra Urban Heat Difference (IUHD) model was constructed. A flowchart showing a simplified workflow of the IUHD-model can be seen in figure 4. The model used the inputs of DSM, DEM and CDSM as well as a within-model created vector-grid to calculate IUHD from the warming effect of the building density and the cooling effect from vegetation.

As mentioned in the literature review, one metric for describing building density is the Height-Width ratio (H/W-ratio). The H/W-ratio can be used to calculate the maximum UHI-effect in built-up areas (eq. 1). Here, the H/W-ratio was calculated with the following equation (2) (Lindberg, Grimmond, & Martilli, 2015):

$$H/W = \frac{\lambda_W \lambda_p}{2\lambda_p(1-\lambda_p)} \tag{2}$$

where H/W is the Height-Width ratio, λ_w is the wall area fraction and λ_p is the roof area fraction (also known as Plan Area Index, from here on referred to as Plan Area Index).

The wall area fraction (λ_w) was defined with the following equation (3):

$$\lambda_W = \frac{Area_{wall}}{Area_{road} + Area_{roof}} \tag{3}$$

where λw is the wall area fraction, $Area_{wall}$ is the wall area, $Area_{road}$ is the road area and $Area_{roof}$ is the roof area (Lindberg et al., 2015).

To calculate the wall area, the height of walls needed to be calculated. This was done via an algorithm in the *Urban Multi-Scale Environmental Predictor* (UMEP)-plugin. The algorithm calculated wall heights for each building, using the DSM as input layer. The wall heights were appended to the 100 x 100 meter vector-grid created in the model, where the sum of wall heights within each grid cell was calculated. The grid was used for the rest of the calculations. With the sum of wall heights within each grid cell, the wall area was calculated. The equation (4) used to derive wall area was:

$$\text{Wall area} = \text{Wall height} * \text{pixel resolution} \qquad (4)$$

Since the pixel size of the DSM was 1 meter, the wall area and the wall height were identical.

The Plan Area Index (λ_p) of buildings was calculated via an UMEP-algorithm which calculates a variety of urban-morphological parameters from digital surface models. The 100 x 100 meter grid was used as input, which meant that the grid now contained all necessary parameters to calculate H/W-ratio, as it is described above (eq. 2). As there were some extreme values of H/W-ratio, the H/W-ratio was normalized, meaning that all H/W-values > 3 was set to 3. Afterwards, the warming effect from H/W-ratio was calculated via eq. 1.

Urban-morphometric parameters were calculated for the CDSM as well, to retrieve the morphometric characteristics of the vegetation. Again, with the 100 x 100 meter grid as input. The parameter of interest was the Plan Area Index (λ_p), which indicates the area of vegetative surface relative to total ground area in each grid cell. The vegetation λ_p (from now on referred to as λp_{veg}) could then be used to calculate the cooling effect of trees, via the equation (5) from Krayenhoff et al., 2021):

$$\text{Tree cooling effect} = (\lambda p_{veg} / 0.1) * 0.3 \qquad (5)$$

The tree cooling effect was subtracted from the H/W-warming effect to get the IUHD, via the following equation (6):

$$\text{IUHD} = \text{H/W-warming} - \text{Tree cooling effect} \qquad (6)$$

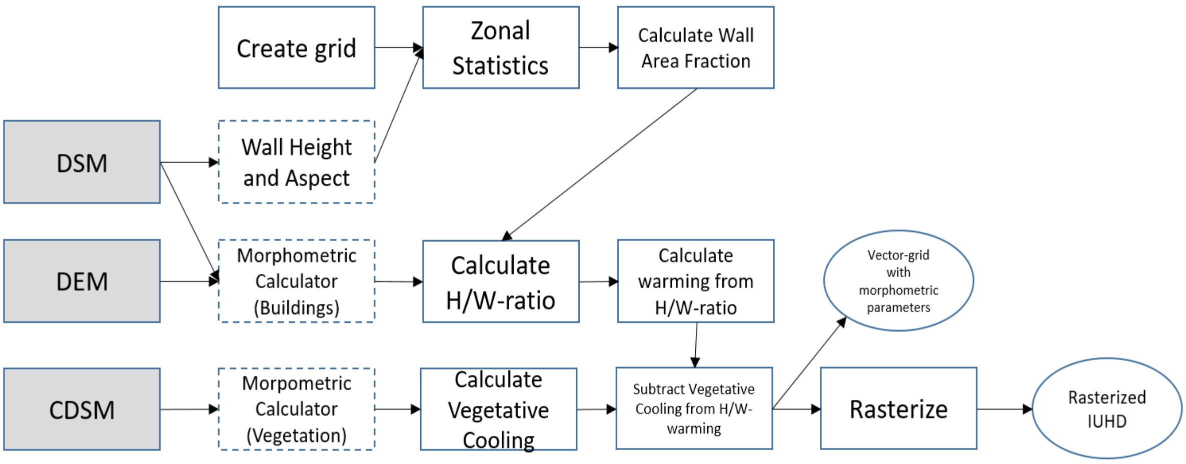

Figure 4. A flowchart showing a simplified version of the IUHD-model. Grey boxes indicate input data. White boxes indicate geoprocessing algorithms. White boxes with dashed outlines indicate algorithms from the QGIS-plugin *Urban Multi-scale Environmental Predictor (UMEP)*. Circles indicate output data.

There were two outputs from the IUHD-model. Firstly, the vector-grid with morphometric parameters for buildings and vegetation. Secondly, a rasterized version of the vector-grid with IUHD-values burnt in (figure 5). The IUHD-raster was used in the oviposition model. The vector-grid was used in the adult model.

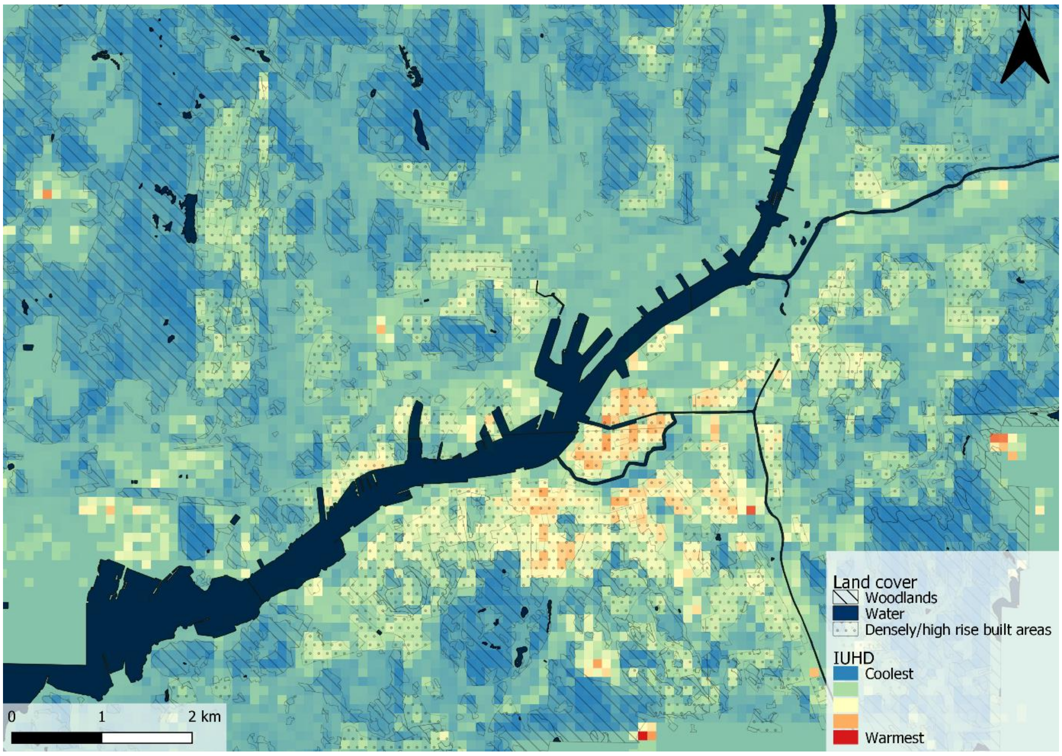

Figure 5. One of the outputs from the IUHD-model, with a vector land cover layer overlain to visualize the spatial patterns of air temperature differences from the model. Note that the input data for the model is of much higher resolution than the vector data used here for visualization.

4.2.1.2 Oviposition model

Cx. pipiens are experts at finding oviposition sites in urban areas and they can lay their eggs in a variety of small water containers if they remain undisturbed. Due to this high adaptive capacity of the *Cx. pipiens*, as well as the utilized water containers being smaller-than-microscale, the complexity was hard to grasp via a model. Therefore, a simplified model of oviposition suitability was produced. The model reclassifies land use, land cover and IUHD, depending on their suitability as oviposition sites for *Cx. pipiens*. The input data and their application can be seen in table 2.

Table 2. The input data for the oviposition model and their application.

Data	Application
NMD Land Cover	Locate suitable land cover (e.g., vegetation)
Digital Surface Model (DSM)	Locate flat roofs
Buildings	Locate residential gardens and flat roofs
Land use vector	Locate industrial areas
NMD Land use	Locate suitable land use (e.g., cemeteries, allotment gardens)
Intra Urban Heat Difference (IUHD)	Locate relatively warmer areas

The flowchart in figure 6 shows a simplified version of the workflow of the model. The NMD-data was used for both land use and land cover. Flat roofs (slope <8°) were located via the DSM and the vector-dataset of buildings, as oviposition sites can be found on roofs as well. To locate residential gardens, residential stand-alone houses were extracted from a vector-dataset of buildings. A buffer zone was created around the residential houses, and the buffer was then rasterized, to indicate residential gardens. The model reclassified land cover and land use to a scale of 1-10, by how suitable the different land uses, and land covers are as oviposition sites for mosquitoes. Suitable land *uses* are, e.g., cemeteries, allotment gardens and residential gardens, whereas less suitable land *uses* are, e.g., airports and motor racetracks. Suitable land *covers* are, e.g., deciduous forests on wetland, and less suitable land *covers* are, e.g., roads, open water, and impervious surfaces. The reclassified land use and land covers were added together, and then divided by 2 to get a joint metric for land cover and land use. The model also reclassified the IUHD-values to a scale 1-10, where relatively warmer areas were given higher values. The complete reclassifications of land cover, land use and IUHD can be seen in appendix 1.

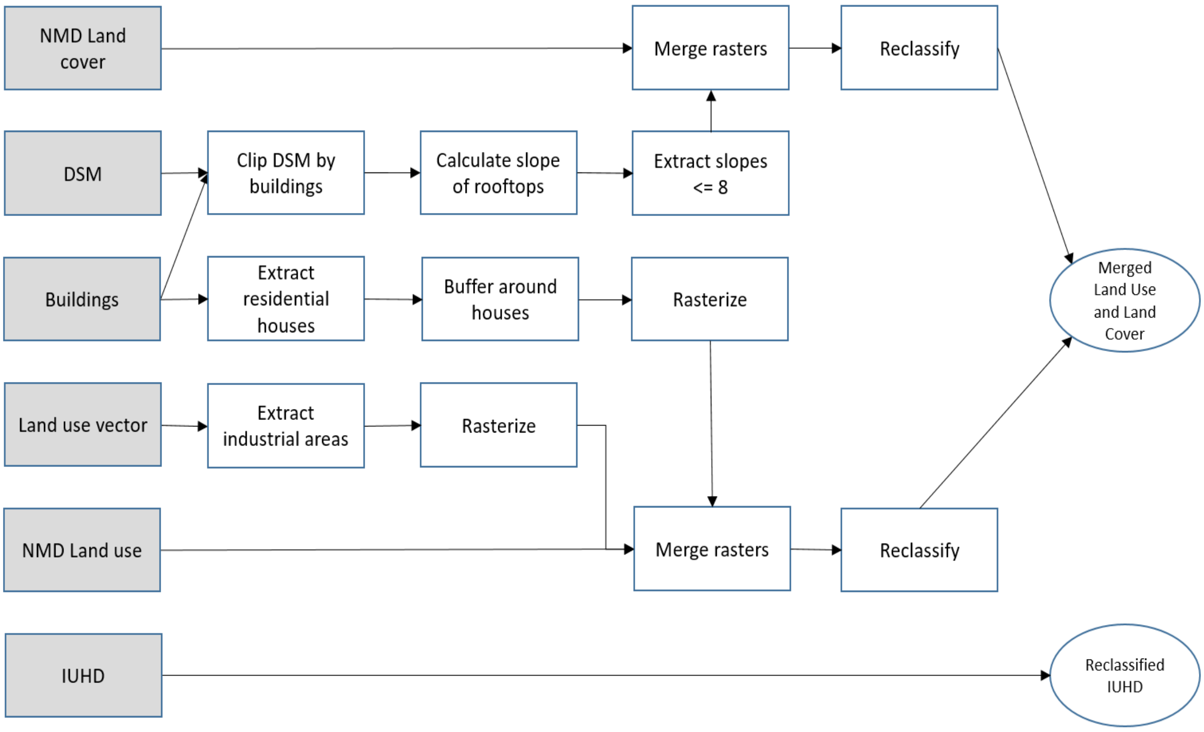

Figure 6. A flowchart showing a simplified version of the oviposition-model. Grey boxes indicate input data. White boxes indicate geoprocessing algorithms. Circles indicate output data.

4.2.1.3 Heatmap model

The heatmap model used the output from the oviposition WMCA (described in section 4.2.2.1) to create a heatmap of oviposition sites in Gothenburg. The heatmap was used as input in the adult WMCA, as adult mosquitoes are likely to be present in larger numbers in areas that are in proximity to suitable oviposition sites.

The model assigned different oviposition-WMCA values into different workflows, where values larger than 6 went into one workflow, values between 5 and 6 went into another, and so on. The last workflow had WMCA-values between 1 and 2. The raster pixels were turned into vector points, and then a heatmap-algorithm was performed with a maximum distance value of 500 meters. As mentioned in the literature review, *Cx. pipiens* seldom fly more than 500 meters from their birthplace (European Centre for Disease Prevention and Control, 2020; Verdonschot & Besse-Lototskaya, 2014). Higher oviposition-WMCA values were given a higher weight, as higher oviposition WMCA-values were indicative of higher suitability for oviposition. The different heatmaps were combined to one, by adding them together and dividing by 6 (the number of individual heatmaps). A map of the output from this model can be seen in appendix 3. The output from this model was used in the adult model.

4.2.1.4 Adult model

The adult model uses several inputs, with each one being an indicator for mosquito suitability in some way. The input data of the adult model and their application can be seen in table 3.

Table 3. The input data for the adult model and their application.

Data	Application
Land Cover vector	Locate suitable land covers (e.g., areas with low houses)
Heatmap	Locate oviposition-risk areas
NMD Land Cover	Locate suitable land cover (e.g., vegetation)
NMD Object heights 0.5-5 meters	Locate suitable vegetation heights
NMD Object heights 5-45 meters	Locate suitable vegetation heights
Leaf Area Index	Locate highly vegetated areas
Morphological grid	Locate morphologically suitable areas
Digital Elevation Model (DEM)	Locate less wind affected areas

A flowchart showing a simplified version of the adult model can be seen in figure 7. The main purpose of the adult model was to create, merge and reclassify datasets. The reclassification was to a scale 1-10, after how suitable they are for adult mosquitoes. However, not all outputs utilize the entire scale. The complete reclassifications for each dataset can be seen in appendix 2.

Starting from the top of figure 7, the vector land use dataset was reclassified and rasterized. More suitable areas were, e.g., urban woodlands. Less suitable areas were, e.g., densely built-up areas. The heatmap (the output from the heatmap model, section 4.2.1.3) was reclassified, using an equal interval reclassification. Higher heatmap-values were given higher reclassification-values as adult mosquitoes are likely more prevalent in areas in proximity to their birthplace. The NMD object heights were merged. Pixels containing vegetation was extracted from the NMD Land Cover-data, which was then joined with the merged object height-raster to obtain the heights of the vegetation. This layer was then reclassified. In general, lower vegetation was given higher reclassified values and higher vegetation was given lower reclassified values as *Cx. pipiens* seldom occupy very tall trees. The NMD land cover is reclassified. Higher reclassified values were given to, e.g., vegetated areas, lower reclassified values were given to, e.g., roads, water, and impervious surfaces. NMD land cover was used to find ocean pixels. The ocean pixels were used to calculate distance from ocean, which was used to calculate the wind reduction by increasing distance from the ocean by the equation (7):

$$\text{Wind speed} = u_{ref} * e^{0.015 * dist} \qquad (7)$$

where u_{ref} is the wind speed at a reference point (2.6 is chosen here, which is the mean wind speed for Gothenburg), e is Euler's constant and dist is the distance from the ocean (in kilometers). The equation is courtesy of Holmer and Linderstad, (1985)

The wind reduction by increasing distance from the ocean was reclassified. Lower wind speeds (further from the ocean) were given higher reclassified values, and higher wind speeds (closer to the ocean) were given lower reclassified values. The DEM was used together with the morphological grid to get the mean altitude of the grid cells. The mean altitude was used to calculate how the wind speed is affected by altitude, using the wind power law, via the equation below (8):

$$u = u_r \, (z / z_r)^{a} \qquad (8)$$

where u is the wind speed at height z, u_r is the known wind speed at the reference height z_r and a is the power exponent. 2.6 was used as the known wind speed, due to it being the mean wind speed in Gothenburg. 2 was used as the reference height. The power exponent a was given the value 0.2.

The morphological grid contains the vegetation Plan Area Index (λp_{veg}), which was used as an indicator for bird-rich areas. As the *Cx. pipiens* is ornithophilic, they will likely look for bloodmeals in areas with a higher number of birds. A higher degree of canopy (or vegetation) cover has been found to be an indicator for higher species richness, as well as higher number of individual birds (Hedblom & Söderström, 2010). The λp_{veg} was reclassified, where higher λp_{veg} -values are given higher reclassified values and vice versa.

The *Cx. pipiens*, like other mosquitoes, are affected by wind patterns in their movement, and are less likely to be found in areas with strong winds. The morphological grid contains the parameter Frontal Area Index (λ_F) of both vegetation (λ_{Fveg}) and buildings ($\lambda_{Fbuildings}$). λ_F is a metric which indicates the area of building walls, or tree trunks, facing a specific wind direction relative to total ground area (Wong & Nichol, 2013). Higher values of λ_F indicate areas where wind speeds are reduced due to interference of buildings or vegetation (ibid). The Leaf Area Index (LAI) is also an indicator of wind reduction from vegetation; however, a porosity value must first be added to the LAI. The foliage state of vegetation affects the porosity (and therefore the wind reduction) of the vegetation (Kent, Grimmond, & Gatey, 2017). More foliage gives lower porosity, less foliage gives higher porosity. The equation for merging LAI, λ_{Fveg} and $\lambda_{Fbuildings}$ can be seen below (9).

$$\text{Wind reduction} = (((\text{LAI} * \text{porosity value}) * \lambda_{Fveg}) + \lambda_{Fbuildings}) / 2 \qquad (9)$$

where LAI is the Leaf Area Index, λ_{Fveg} is the Frontal Area Index for vegetation and $\lambda_{Fbuildings}$ is the Frontal Area Index for buildings. A porosity value of 0.6 is chosen for the LAI, based on a default value from the UMEP-plugin.

In their search for suitable areas to inhabit, *Cx. pipiens* often look for vegetated areas which provide both shade and a higher humidity than non-vegetated areas. As an indicator for shade and humidity, LAI was used. LAI was found to be a good indicator for several ecosystem functions in a report from the University of Gothenburg (Andersson-Sköld, Klingberg, Gunnarsson, & Thorsson, 2018). They found that LAI is an indicator for shade and humidity. The LAI-data was reclassed, where higher LAI-values are given a higher reclassed value.

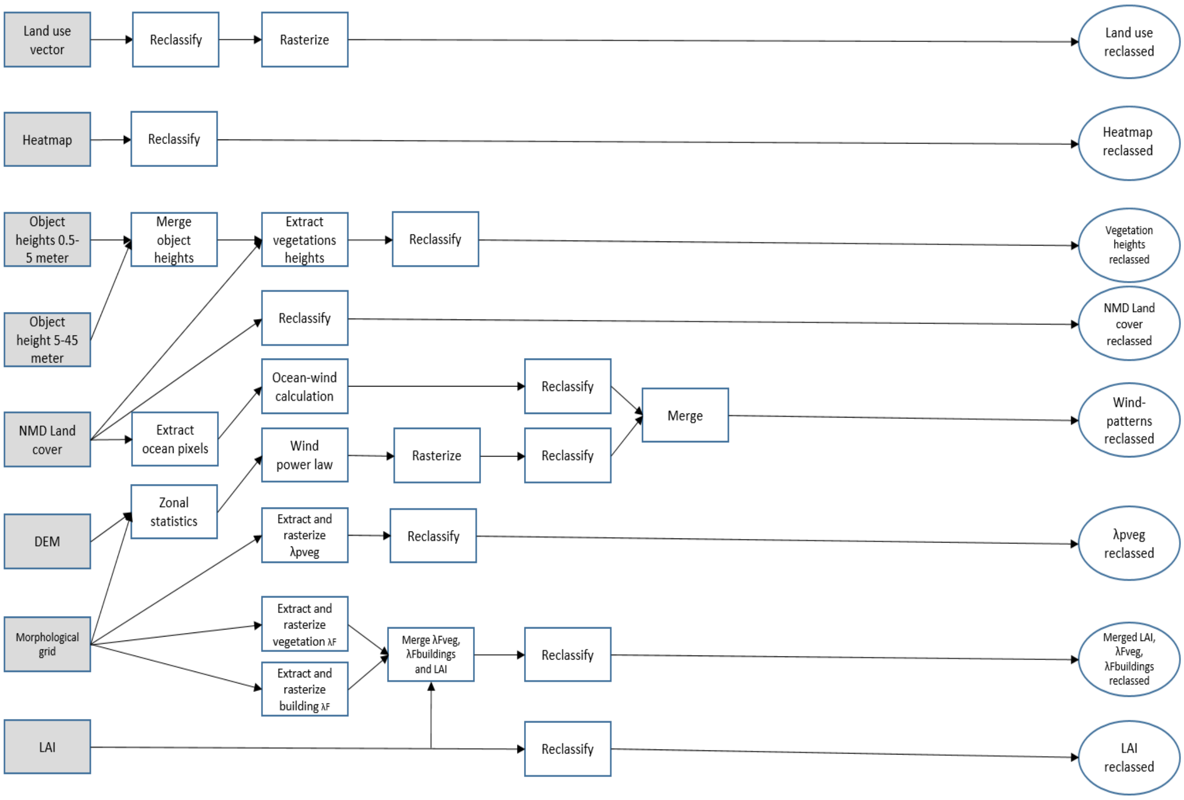

Figure 7. A flowchart showing a simplified version of the adult-model. Grey boxes indicate input data. White boxes indicate geoprocessing algorithms. Circles indicate output data.

The output datasets of the adult model, and what they are an indicator for can be seen in table 4.

Table 4. The output datasets from the adult model, and what they are an indicator for.

Data (reclassed)	Indicator for
Land use from vector	Different urban land use (e.g., densely built buildings, woodlands)
Heatmap	Oviposition hotspots
Vegetation heights	Vegetation height suitability
NMD Land cover	Land cover suitability
Ocean-altitude wind patterns	Large scale wind reduction
λp_{veg}	Bird rich areas
Merged LAI, λ_{Fveg} and $\lambda_{Fbuildings}$	Small scale wind reduction
LAI	Shade, moisture, wind reduction

4.2.2 Weighted multi criteria analysis (WMCA)

A Weighted Multi Criteria Analysis (WMCA) was used to combine the different reclassed datasets to locate areas in Gothenburg with relatively higher and lower suitability for the *Cx. pipiens*, both regarding oviposition and adult distribution.

The WMCA was performed in the QGIS Plugin *Weighted Multi Criteria Analysis – WMCA*, developed by (Carvalho Neto & Benedetti, n. d.). The plugin makes it possible to combine different rasters, providing individual grades to the raster values and different weights to each raster to get a joint analysis for the provided criteria. Before the WMCA could be performed, all rasters had to be aligned to the same pixel size and extent.

4.2.2.1 Oviposition WMCA

The WMCA for oviposition sites only had two inputs, namely the IUHD-raster and the combined land use and land cover raster layer. The weights of the two raster layers can be seen in table 5. The reasoning for the weighting was that the *Cx. pipiens* are highly adapted at finding oviposition sites all over an urban area and are therefore not strongly affected by air temperature variations in the city. Therefore, the IUHD-layer was not seen as a decisive parameter, but rather as an indicator for areas where mosquito development may be accelerated due to relatively warmer air temperatures.

Table 5. The weights provided to the raster layers used in the WMCA for oviposition sites.

Raster	Weight
Combined Land Use Land Cover	0.9
IUHD	0.1

4.2.2.2 Adult WMCA

The input data for the adult WMCA and their weights can be seen in table 6.

All raster layers used in the WMCA were of importance. However, not all parameters were equally important. In general, the weights were distributed to give higher weights to well-known and strong indicators (e.g., LAI) and to parameters that will affect mosquito distribution more efficiently (e.g., heatmap and ocean-altitude wind patterns). Subsequently, lower weights were given to parameters that are believed to be important, but not as important as the other parameters.

LAI had the highest weight due to the metric being a strong indicator for shade and humidity. The heatmap was given the highest weight, as *Cx. pipiens* are not believed to fly far away from their birthplace. The land use had medium-high weight due to the parameter being useful in demarcating suitable land uses from unsuitable. The ocean-altitude wind patterns had medium-high weight, due to wind influencing mosquito distribution. λp_{veg} was given medium-high weight, as the *Cx. pipiens* are more likely to inhabit bird-rich areas. The vegetation height had medium-low weight as the level of influence of vegetation heights on the distribution of *Cx. pipiens* is not fully understood. Medium-low weight was given to the merged LAI, λ_{Fveg} and $\lambda_{Fbuildings}$ as the wind reduction from vegetation is already partially given in the LAI-parameter. So, to avoid an overrepresentation of vegetation-parameters, the merged LAI, λ_{Fveg} and $\lambda_{Fbuildings}$-parameter was given lower weight. NMD Land cover had low weight as the parameter was mostly used to mask away unsuitable areas (e.g., roads and water).

Table 6. The weights provided to the raster layers used in the WMCA for adult distribution.

Raster	Weight
LAI	0.18
Heatmap	0.18
Land use	0.13
Ocean-altitude wind patterns	0.13
λp_{veg}	0.13
Vegetation heights	0.1
Merged LAI, λ_{Fveg} and $\lambda_{Fbuildings}$	0.1
NMD Land cover	0.05

4.2.3 Sensitivity analysis

A sensitivity analysis was performed, to examine how the individual parameters influence the results of the adult-WMCA. The WMCA with weights as in table 6 was used as a base scenario. To perform the sensitivity analysis, each individual parameter was tested one at a time by increasing their relative weight. The weight of every other parameter was decreased by 0.02, and that weight was given to the parameter being tested. See table 7 for an example, where the tested parameter was the heatmap. To investigate the difference, the mean value for the output raster layer from the base scenario and the scenarios for each of the tested parameters were derived and compared.

Table 7. An example of the weighting difference from the sensitivity analysis. In this example, the tested parameter was the heatmap, which gained 0.02 in weight from every other parameter.

Parameters	**Base scenario weight**	**New weight**
Heatmap (tested parameter)	0.18	0.32
LAI	0.18	0.16
Land use	0.13	0.11
Ocean-altitude wind patterns	0.13	0.11
λp_{veg}	0.13	0.11
Vegetation heights	0.1	0.08
Merged LAI, $\lambda_F$veg and $\lambda_F$buildings	0.1	0.08
NMD Land Cover	0.05	0.03

4.2.4 Human exposure analysis

The result from the base scenario for the adult-WMCA was compared to population data from Statistics Sweden (in Swedish: *Statistiska Centralbyrån,* acronym SCB). The population data was retrieved from the Swedish Mapping Cadastral and Land Registration Authority, (2021). It was used to locate areas of potentially high human exposure to the *Cx. pipiens*. The population data from SCB was delivered as a vectorized raster with 100 x 100-meter cells. The mean value of the adult-WMCA was calculated for each 100 x 100-meter cell. The mean value of the adult-WMCA and the population of each grid cell was then reclassified to a scale of 1-10. Higher original values were given higher reclassified values. The reclassified values were then joined together with the following equation (10):

$$(\text{Adult WMCA value} + \text{population}) / 2 \qquad (10)$$

5. Results

The results are presented in three subsections. In the first subsection (5.1), the results from the oviposition sites-model and adult distribution-model are presented. In the second subsection (5.2), the result from the sensitivity analysis is presented. In the third subsection (5.3), the human exposure analysis is presented.

5.1 Model results

Presented below are suitability maps for oviposition sites and adult distribution in the entire city of Gothenburg (figure 8). The suitability for both oviposition sites and adult distribution show large intra-urban variations. Regarding oviposition (figure 8a), the lowest suitability is found on roads and in densely built-up areas. Medium suitability is mostly found in industrial areas. The highest suitability for oviposition is found in cemeteries, allotments, and residential gardens. The results from the adult distribution model (figure 8b) indicate lowest suitability in built-up and/or areas with impervious surfaces. The highest suitability is found in vegetated areas, like parks and woodlands.

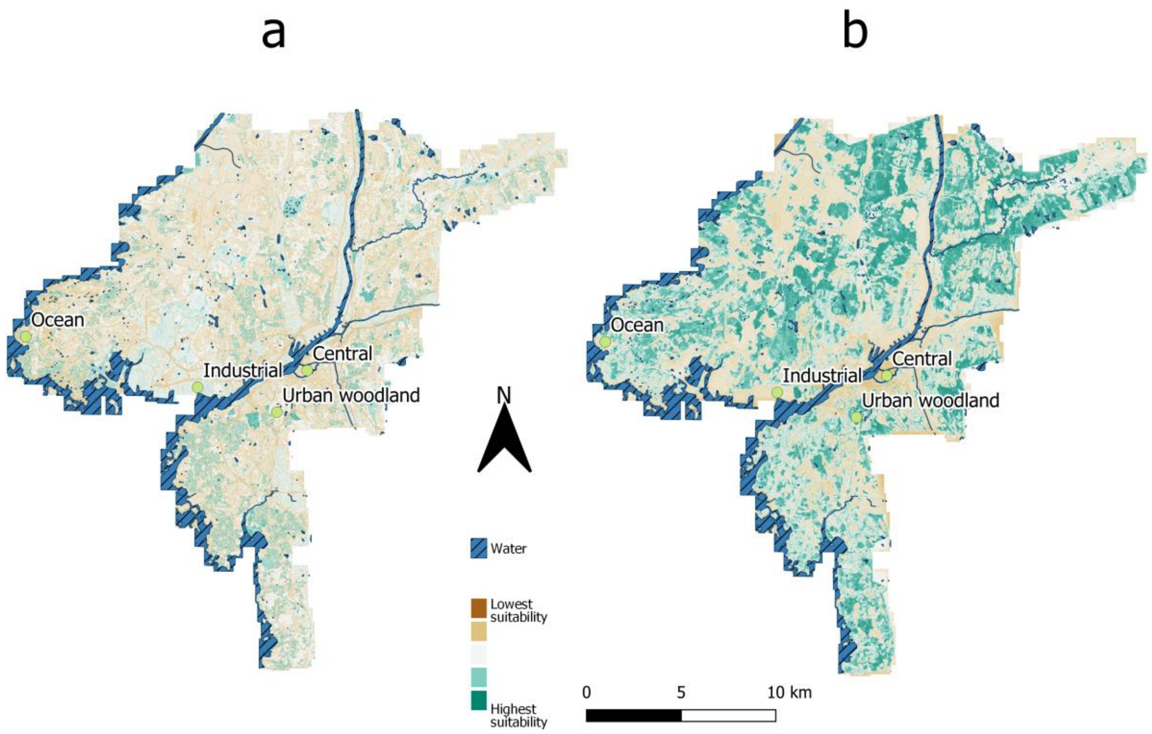

Figure 8. The modelled suitability for oviposition sites (a) and adult distribution (b) in the city of Gothenburg. The points on the map represent the smaller scale study sites.

To provide a better understanding of the results from the model, four smaller areas have been chosen that each represent different locations and urban structures in Gothenburg. The smaller areas are presented below, for both the oviposition and adult distribution models.

5.1.1 Central Gothenburg, densely built.

Figure 9 shows the oviposition suitability map (9b) and the adult distribution map (9c) over central Gothenburg.

The oviposition-map indicates highest suitability in proximity to churches, cemeteries, and residential gardens, while lowest suitability is found in paved or built-up areas. Medium suitability is seen in the industrial area on the north side of the Göta River. Note that churches get highest suitability due to the input land use data (from NMD) classifying all churches as cemeteries.

Regarding the adult distribution, highest suitability is found in vegetated areas, with a high proportion of trees. Roads, paved areas, and built-up areas (which dominate the urban structure of the central parts of Gothenburg) have lowest suitability.

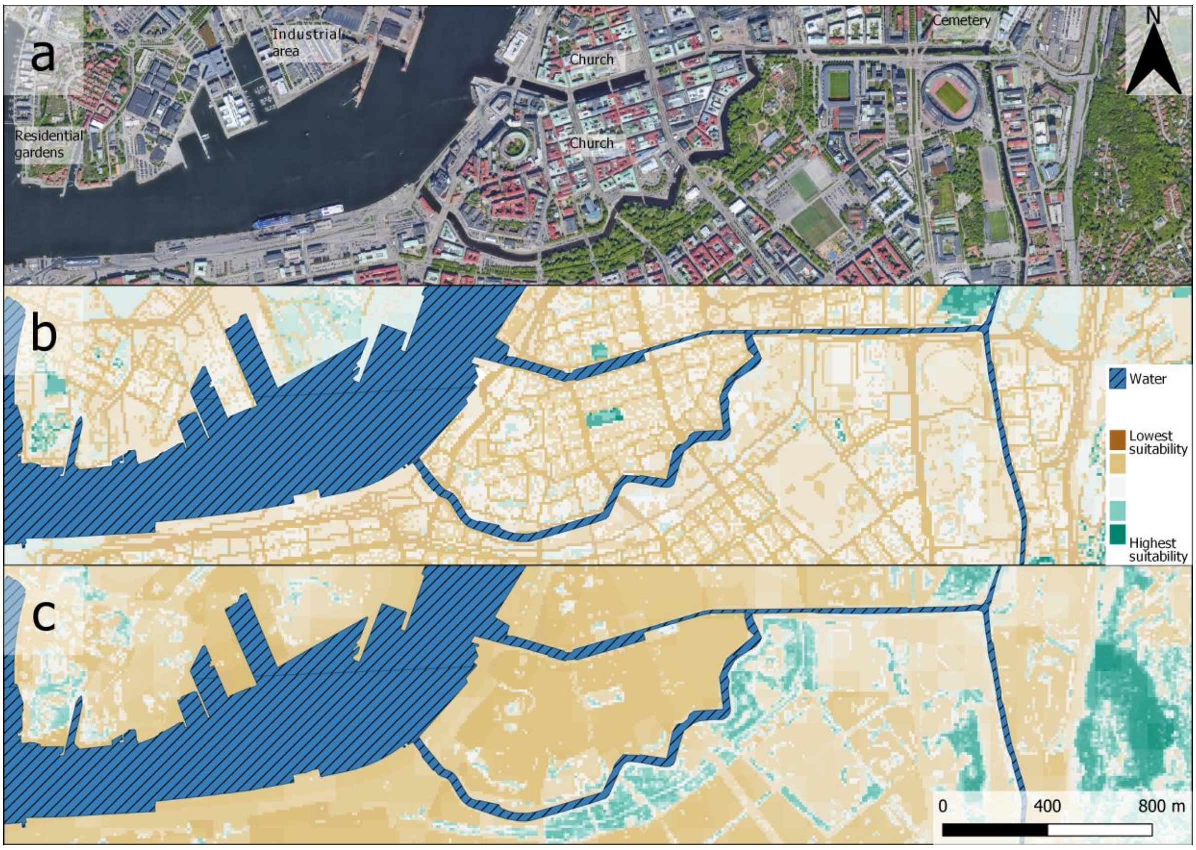

Figure 9. A satellite image for reference (a), the modelled suitability for oviposition sites (b) and adult distribution (c) in central Gothenburg. Satellite image taken from Google Maps.

5.1.2 Urban woodland

Figure 10 shows the oviposition suitability map (10b) and the adult distribution map (10c) over an area surrounding an urban woodland.

Regarding oviposition, highest suitability is found in a cemetery, residential gardens, and an allotment. Lowest suitability is found on roads and in densely built-up areas. The urban woodland has low-to-medium suitability.

The suitability for the adult distribution shows highest suitability in the vegetated areas, e.g., the urban woodlands. Lowest suitability is found on roads and in densely built-up areas.

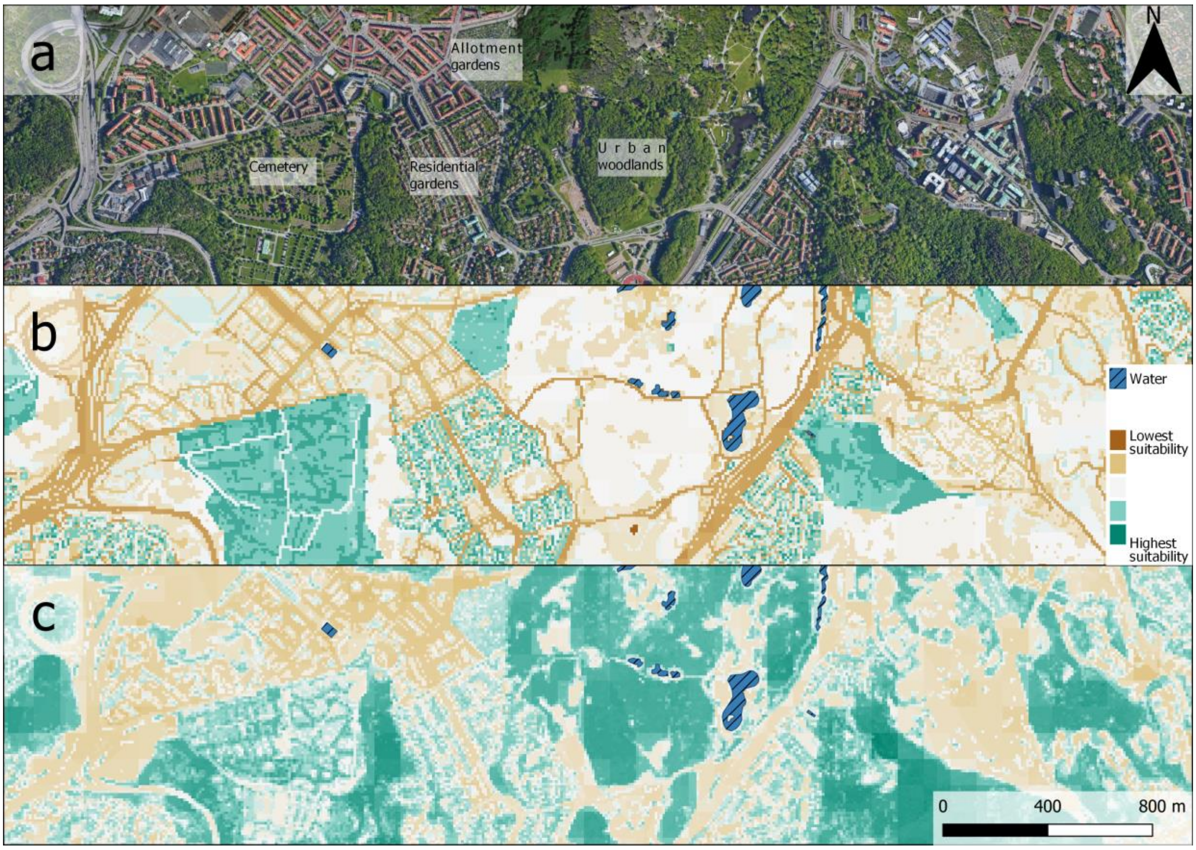

Figure 10. A satellite image for reference (a), the modelled suitability for oviposition sites (b) and adult distribution (c) in an area surrounding an urban woodland. Satellite image taken from Google Maps.

5.1.3 Ocean-near area

Figure 11 shows the oviposition suitability map (11b) and the adult distribution map (11c) over an ocean-near area.

Regarding the oviposition suitability, highest suitability is found in residential gardens and in a grazing area. Lowest suitability is seen on roads and in areas with exposed bedrock.

The highest suitability for adult distribution is seen in densely vegetated areas. Lowest suitability is found on roads and in areas of exposed bedrock, especially close to the ocean.

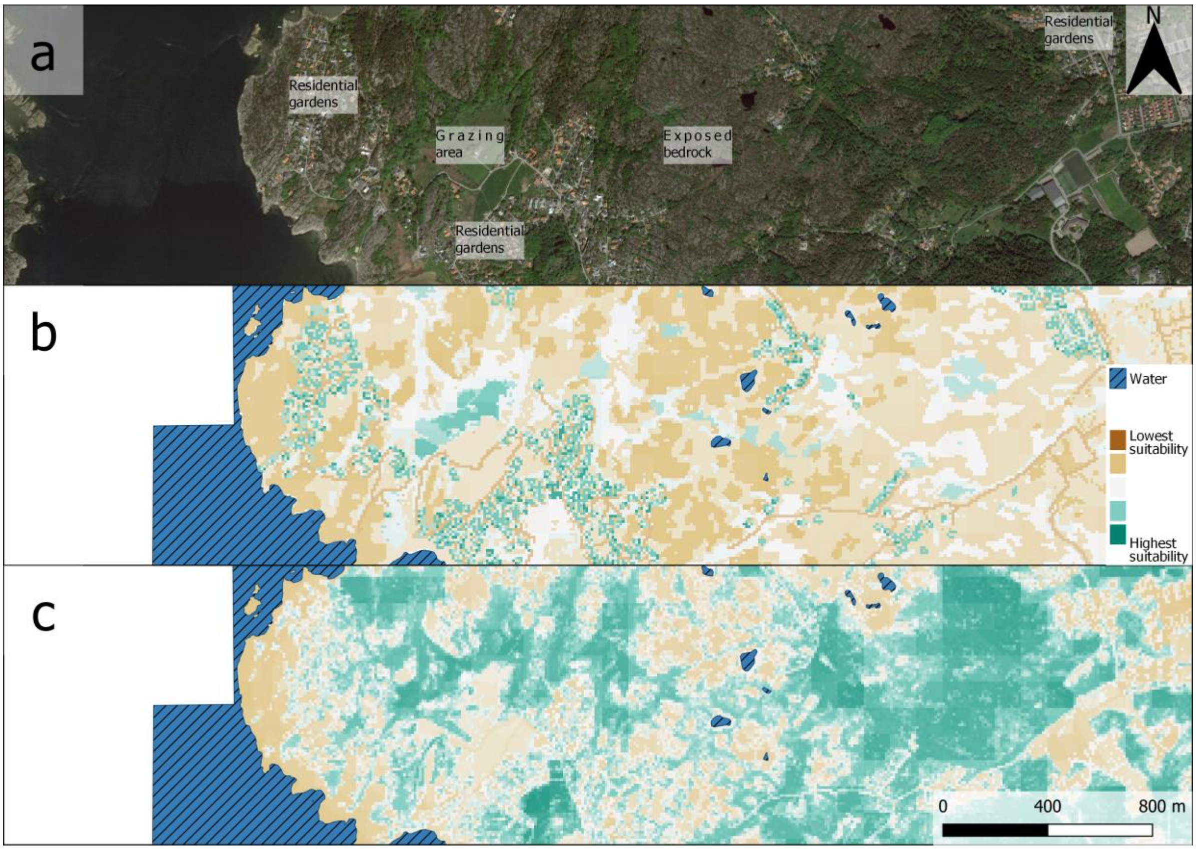

Figure 11. A satellite image for reference (a), the modelled suitability for oviposition sites (b) and adult distribution (c) in an ocean-near area. Satellite image taken from Google Maps.

5.1.4 Industrial area

Figure 12 shows the oviposition suitability map (12b) and the adult distribution map (12c) over an industrial area.

The oviposition suitability map indicates highest suitability in the residential gardens to the east. The industrial area has medium-high suitability. Lowest suitability is seen on roads.

Regarding the adult distribution, highest suitability is seen in the vegetated areas, especially in the densely vegetated area in the southeast. Lowest suitability is found in the industrial areas and on roads.

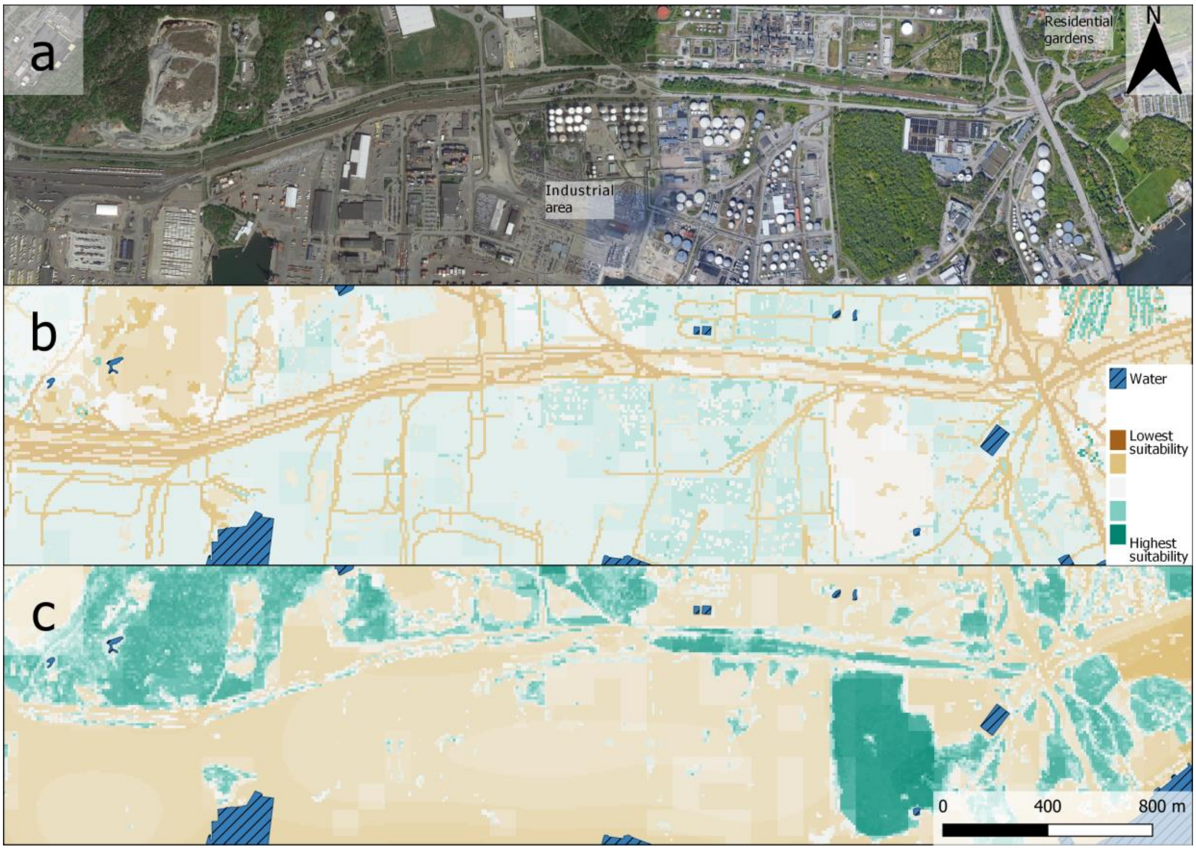

Figure 12. A satellite image for reference (a), the modelled suitability for oviposition sites (b) and adult distribution (c) in an industrial area. Satellite image taken from Google Maps.

5.2 Sensitivity analysis

From the results of the sensitivity analysis (figure 13), the base-scenario has a mean value of 4.62, while the mean values for the different scenarios range from 4.33 to 4.95.

The vegetation heights, LAI, and NMD Land Cover-parameters have mean values closest to the base-scenario (difference in mean value being <= 0.06). The other scenarios have larger differences in mean value compared to the base. The heatmap and land use-parameters show higher mean values than the base scenario, while the λp_{veg}, Ocean-altitude wind patterns and Merged LAI, λ_{Fveg} and $\lambda_{Fbuildings}$ indicate lower mean values than the base scenario.

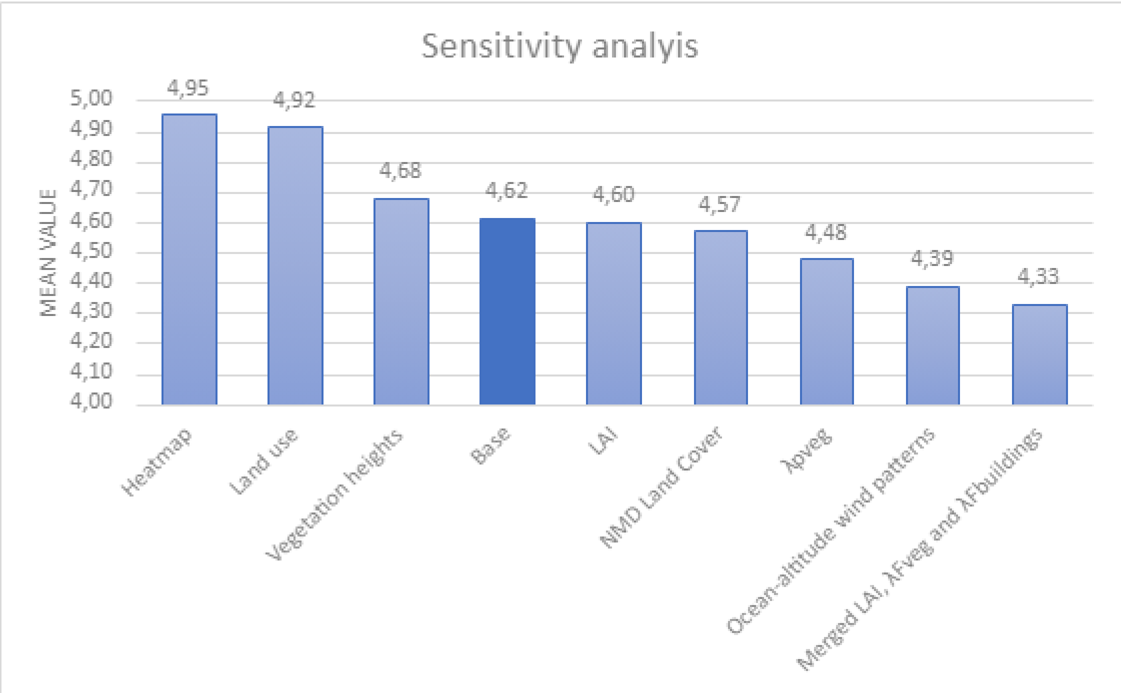

Figure 13. A diagram showing the result from the sensitivity analysis. The different scenarios (X-axis), and their respective mean value (Y-axis) is shown. Note that the base-scenario is of a different hue, to differentiate it from the other scenarios.

5.3 Exposure analysis

The exposure analysis-map can be seen in figure 14. In general, the exposure of mosquito-human interactions is low to medium in Gothenburg, especially in the central parts. Some higher exposure areas can be found in the outer parts of the city, in all cardinal directions. The areas of highest exposure are in the north and northeast.

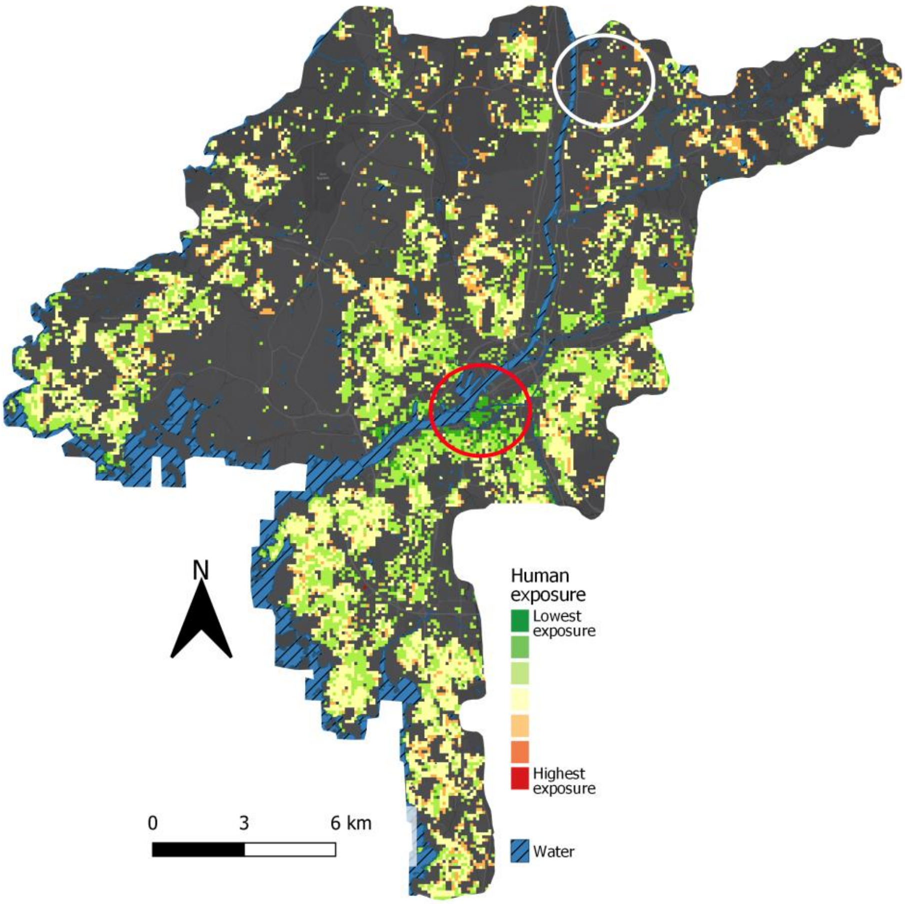

Figure 14. Exposure assessment map for mosquito-human interactions. In general, the exposure in Gothenburg is low to medium. High exposure areas are found in the outer parts of the city, especially in the northeast (white circle). The central parts of the city have low exposure (red circle). Basemap: Esri Gray (Dark).

6. Discussion

This study has developed a modelling workflow that produces suitability maps for the *Cx. pipiens* in the city of Gothenburg, both regarding oviposition sites, and adult distribution. Both models indicate large intra-urban variations, due to, e.g., different land uses, land covers and difference in vegetation density. Areas with highest suitability for oviposition are, e.g., cemeteries and allotment gardens. Lowest suitability for oviposition are found on, e.g., roads and in paved areas. Regarding adult distribution, highest suitability are found in densely vegetated areas, like urban woodlands. Lowest suitability for adult distribution is found on roads and densely built-up areas. The modelled suitability regarding oviposition and adult distribution is in line with previous research (Townroe & Callaghan, 2014; Vezzani, 2007).

6.1 Spatial patterns of mosquito models

6.1.1 Oviposition model

The results from the oviposition-model (figure 9b-12b) indicates that highest suitability for oviposition sites is found in cemeteries, residential gardens, and allotment gardens. Previous research has found especially cemeteries and residential gardens to be highly suitable sites of oviposition for *Cx. pipiens* (European Centre for Disease Prevention and Control, 2020; Rydzanicz, 2021; Townroe & Callaghan, 2014). Allotment gardens have not been researched in the same capacity as the other two, but similar traits are found in allotments as in the other two types of areas: less organized areas with a high likelihood of urban gardening and therefore a higher likelihood of artificial water containers being present. Such areas have suitable conditions for being a hotspot as oviposition sites for the *Cx. pipiens.* Furthermore, Ibañez-Justicia et al. (2018) found allotment gardens to be a highly suitable oviposition site for the *Aedes japonicus japonicus,* a mosquito with similar requirements regarding oviposition as the *Cx. pipiens* (Rydzanicz, 2021).

Medium suitability in the oviposition model was found in industrial areas, which also are areas with a less organized structure and therefore, water gatherings are more likely to be left undisturbed. Water containers found in industrial areas can be, e.g., unused tires and folds in tarpaulins. Since the *Cx. pipiens* can use slightly contaminated water for oviposition (European Centre for Disease Prevention and Control, 2020), and they are experts at finding water gatherings, industrial areas are likely to be utilized for oviposition by the *Cx. pipiens.* Their ability to use contaminated water for oviposition gives them an edge in the competition with other species with similar requirements for oviposition (European Centre for Disease

Prevention and Control, 2020; Vezzani, 2007). Their high degree of adaptability and usage of different urban settings for oviposition is what makes them so prominent in urban environments (Townroe & Callaghan, 2014). So, if water is left undisturbed in an industrial area, the *Cx. pipiens* is likely to find it and use it for oviposition.

Natural oviposition sites in forested areas, such as puddles, ditches, and tree holes, have low to medium suitability. This was a conscious decision, as the focus of the model is on human-influenced urban environments and artificial containers. Furthermore, previous studies have found that the *Cx. pipiens* are more prevalent in artificial containers than in natural environments, due to a lower degree of competition and less risk for predation in the artificial containers (Vezzani, 2007).

Lowest suitability for oviposition is found on roads and in densely built-up areas. Water gatherings are less likely to be found in such areas, as the areas are highly organized and looked after by humans. For instance, a bucket left on the side of a road in the center of Gothenburg will quickly be removed by city cleaning staff. The same bucket is more likely to be left undisturbed in an allotment, as there is less formal maintenance there. Furthermore, water containers used for irrigation in gardening are less likely to be found in densely built-up areas, as such areas are seldom used for urban gardening.

6.1.2 Adult distribution model

The results from the adult distribution model (figure 9c-12c) indicates highest suitability for mosquito distribution in vegetated areas. Previous research indicates that adult *Cx. pipiens* mostly are found in vegetated areas, like urban parks, woodlands, and cemeteries (Rydzanicz, 2021; Vezzani, 2007). The results show that suitability increases with increased vegetation density. The lowest suitability is found in densely built-up areas in the central part of Gothenburg (figure 9). Although the *Cx. pipiens* is highly adaptable and is found in all kinds of environments (Townroe & Callaghan, 2014), densely built-up areas lack the necessary traits that the *Cx. pipiens* need. There is less vegetation, meaning less shade, less humidity, and less bloodmeals (in the form of birds). So, even if there is a possibility for the *Cx. pipiens* to venture off into different urban areas, they are most often found in vegetated areas, especially in vegetated areas in proximity to their birthplaces, which the model simulations show.

6.2 Sensitivity analysis

The sensitivity analysis (figure 13) indicates that the modelled suitability is affected when the weights of the parameters are altered, as differences in suitability-mean values are seen. How big the differences are, compared to the base scenario, depend on the parameter being tested. To explain and discuss the sensitivity analysis further, the parameters of the study will be split into three groups. The first group is *strictly-vegetation-parameters*. The parameters in this group are LAI, Vegetation heights, λp_{veg}, and NMD Land Cover. These parameters indicate highest suitability in vegetated areas, and lowest suitability in non-vegetated areas. The second group is *partly-vegetation-parameters.* The parameters in the second group are Merged LAI, λ_{Fveg} and $\lambda_{Fbuildings}$, and Land Use. These parameters indicate highest suitability in vegetated areas, but they also indicate somewhat higher suitability in non-vegetated areas, e.g., densely built-up areas for Merged LAI, λ_{Fveg} and $\lambda_{Fbuildings}$. The third group are the *non-vegetation-parameters*. The parameters are Ocean-altitude wind patterns and the heatmap. These parameters are not affected by vegetation in any way.

Regarding the first group (*strictly-vegetation-parameters*) the sensitivity analysis (figure 13) indicate that when increasing their respective weight, they have similar mean values as the base scenario. This indicates that vegetated areas are well represented in the model, as an altering of the weight of the aforementioned parameters does not lead to a major difference in mean value. However, the λp_{veg} -parameter behaves differently from the other vegetation-parameters, as the λp_{veg} -scenario has lower values than the base. This is likely a cause of the spatial resolution, as the original cell size of λp_{veg} is 100 meters, while the other vegetation parameters have smaller original cell sizes (10 meters and 1 meter). Therefore, the spatial patterns of the λp_{veg} -parameter differ from the spatial patterns of the other vegetation parameters.

The second group (*partly-vegetation-parameters*) indicate that vegetated areas have highest suitability, but these parameters also give higher suitability to other, non-vegetated areas. For instance, the Merged LAI, λ_{Fveg} and $\lambda_{Fbuildings}$-parameter indicate highest suitability in vegetated areas, as vegetated areas provide a substantial reduction in wind speeds. The parameter also has higher suitability in densely built areas, as wind speeds are reduced by high building density as well (Wong & Nichol, 2013). The sensitivity analysis (figure 13) shows lower values for the Merged LAI, λ_{Fveg} and $\lambda_{Fbuildings}$-scenario, which is likely caused by the parameter being the only parameter indicating densely built-up areas as suitable. Therefore, the spatial patterns of suitability in the scenario are altered, compared to the base scenario, with densely built-up areas getting higher suitability than in the base. A change in spatial patterns is the cause for the difference in mean value seen in the sensitivity analysis.

When altering the weights of the *non-vegetation-parameters* (heatmap and ocean altitude wind patterns), large differences in mean value are seen (figure 13). This is caused by these parameters being alone in providing a specific spatial pattern of suitability. For instance, the heatmap is the lone parameter to give highest suitability around, e.g., every cemetery. Opposite of the vegetation parameters, where, LAI, NMD Land Cover, λp_{veg} and Vegetation heights all indicate higher suitability for vegetated areas, and lower suitability for non-vegetated areas. So, a higher weight to the heatmap-parameter will lead to the spatial patterns of suitability from the heatmap getting higher value in the model output, leading to a difference in mean value, seen in the sensitivity analysis.

6.3 Exposure analysis

The spatial patterns of the exposure analysis show that, generally, the human exposure to *Cx. pipiens* in Gothenburg is low to medium (figure 14). Especially in the central part of Gothenburg, humans have low potential exposure to *Cx. pipiens*. This is caused by lower suitability for the *Cx. pipiens*, due to the inner city being densely built, with less vegetation and a higher degree of impervious areas. The higher potential exposure that is seen in the outer parts of Gothenburg, especially in the northern parts, is likely caused by an increased suitability for *Cx. pipiens* in conjunction with larger populations. The suburbs are often densely populated as well as highly vegetated, which gives a higher human exposure to mosquitoes. However, the exposure may increase in the future. As (Townroe & Callaghan, 2014) argues, a warming climate in conjunction with a possible increased usage of water collectors and containers in residential gardens may lead to changed dynamics in mosquito-human interactions, with potentially more interactions in the future. There is no data indicating that water containers in gardens have increased in Gothenburg or Sweden. However, droughts do strike Sweden, the most notable in recent years in 2018 during which there was a ban on irrigation in many Swedish cities (Svenskt Vatten, 2018). The Swedish Food Agency has a list of recommendations on how to preserve water in drought-prone areas (Swedish Food Agency, 2020). One recommendation is to start collecting rainwater in the spring season for watering of plants. Which is a good solution for the purpose of saving water, however it may lead to increased oviposition sites for the *Cx. pipiens* and other species of mosquitoes. So, with a warmer and more unpredictable climate, rainwater collectors will likely become more common, which gives more sites for oviposition for the *Cx. pipiens* in urban areas. Furthermore, warmer air temperatures accelerate the development from egg to adult for the *Cx. pipiens* (Townroe & Callaghan, 2014). Warmer air temperatures also increase the potential for viruses and pathogens to develop in the *Cx. pipiens* and other species of mosquitoes (European Centre for Disease Prevention and Control, 2020; Petrić et al., 2017). This leads to a potential for increased interactions between humans and *Cx. pipiens* in a warmer and more unpredictable climate, and the *Cx. pipiens* will in the future have a higher likelihood of carrying diseases. Although this study has focused on the *Cx. pipiens,* which is not a significant biting nuisance for humans, it should be noted that the breeding sites of *Cx. pipiens* are also suitable for other species of mosquitoes, like the invasive species *Aedes japonicus japonicus* and *Aedes albopictus* (Rydzanicz, 2021). These *Aedes* species are prominent vectors of different diseases, and are a bigger biting nuisance for humans, but they are presently not found in large numbers in Sweden. However, the ongoing climate change may lead to an establishment of invasive species in new areas (Petrić et al., 2017; Rydzanicz, 2021).

6.4 Methodological discussion and potential improvements

The models produced suitability maps for oviposition and adult distribution that are in line with previous research. However, due to the complexity of the field, improvements to the methodology and the collected data could be made to develop these models further. As this study was a methodological development, there was a lack of previous research meaning that there were no guidelines to follow. The work-process presented in the study is proven successful, but further research is needed to validate the model and improve it further.

The sensitivity analysis (figure 13) indicates that vegetated areas might be overrepresented. This is implied by a lack of difference in the mean values of the sensitivity analysis for the *only-vegetation-parameters* and the base scenario. When looking at the parameters and their weights, in table 6, the high influence of vegetated areas is evident. Parameters that indicate highest suitability for vegetated areas (LAI, Vegetation heights, Land use, Merged LAI, λ_{Fveg} and $\lambda_{Fbuildings}$ λp_{veg} and NMD Land cover) make up a total weight of 0.69. Although the *Cx. pipiens* is more likely to inhabit vegetated areas, such high weight for vegetation parameters leaves the other parameters with only a small influence. However, each of the vegetation-parameters are indicators of different aspects connected to *Cx. pipiens*-suitability and were found to be necessary. Furthermore, parameters like the Land Use indicate highest suitability for vegetated areas, but it also gives somewhat higher suitability for, e.g., industrial areas and open ground, which is not represented by any other parameter. But with a different weighting, a more nuanced picture might have been gained, where the influence of non-vegetation parameters could have been larger.

Industrial areas were given medium suitability in the oviposition model. However, an argument can be made that figure 12b overestimates the importance of industrial areas, as the entire industrial area is classified as moderately suitable. Large parts of the area are likely unsuitable due to a high degree of large, empty, paved surfaces. But at the same time, the industrial area has a higher probability of providing small scale water gatherings for the *Cx. pipiens* to inhabit. This boils down to a question of scale, as the water gatherings utilized by the *Cx. pipiens* are "smaller-than-microscale", meaning they cannot be located with the method utilized in this study. With the data and knowledge at hand the best solution was to classify the entire industrial area as moderately suitable, due to a higher possibility of artificial water containers being present there than in other parts of the city. This issue of scale is true in other hotspot areas as well. Entire cemeteries or allotment gardens are not suitable for oviposition, which the maps indicate, but the chance of finding *Cx. pipiens* egg and larvae are bigger in these areas than in other areas.

The heatmap-model could be further developed to implement a cost-variable in its production, i.e., that there is a simulated cost connected to moving over different land covers for the mosquitoes. E.g., a higher cost to move over large, paved surfaces, buildings, and waterways, as *Cx pipiens* seldom fly over such areas. Lower costs would be given to vegetated surfaces, as these areas are more suitable as flight paths for the *Cx. pipiens*. A test was made to construct a cost raster instead of a heatmap, without satisfactory results. With the limited timeframe, a heatmap was the best option. However, an argument in favor of the heatmap could be made. Since highly suitable areas of oviposition are found all over the city, a cost-parameter might not have improved to model significantly. Even though the mosquitoes born, e.g., on the south side of the Göta River cannot fly to a vegetated area on the north side, which the heatmap produced here indicates, the mosquitoes born on the north side will fly to the vegetated area on the north side. So, the heatmap produced in this study is therefore a strong and relevant parameter but could be tweaked for potential improvements.

At present, the model gives high suitability to small patches of trees, e.g., along avenues, which will not provide suitable living conditions for *Cx. pipiens,* due to the trees not giving enough shade, shelter, or humidity. An effort was made to remedy this issue via using a majority filter on the LAI (which gave high values to patches of trees). The majority filter removed single standing trees, and some rows of trees, but not all street trees were removed, as can be seen in the adult distribution over central Gothenburg (figure 9c).

The aim of creating a nationally applicable model was somewhat successful, as most of the data has national coverage. The elevation models and the LAI are lacking national coverage, but they are produced from LiDAR-data, which is nationally available. Therefore, the elevation models and the LAI used in this study can be produced on a national scale. Moreover, most municipalities in Sweden have local GIS-departments, which often have local elevation models, like the one used in this study.

Another issue that may distort the results is that the LiDAR-data is from 2010. The urban structure of Gothenburg has been altered in the years that have passed since then, and the outcome of the models is likely affected by this. This is seen in the suitability map around an industrial area (figure 12) where the satellite image shows a quarry in the northwest part of the map. The suitability map for adult distribution (figure 12c) indicates the area as highly suitable, which it should not do for a quarry. When looking at older satellite images, it was revealed that the quarry is newly developed, and that there was dense forest in the area previously. So, the LAI-data (from 2010) indicated it as highly suitable, which is incorrect. However, this study aims at testing a methodology and producing a model, and not at producing a completely accurate picture of the current situation. Therefore, the somewhat outdated datasets do not affect the outcomes of the study in a significant way.

6.5 Future research

As this study has focused on methodology development, the veracity of the results is difficult to confirm. However, the results are promising, and indicates that the produced models fulfill the aim of the study. However, a validation study is needed to evaluate the performance of the model. The validation should be a sampling study of both eggs, larvae and adults of the *Cx. pipiens* in areas defined as highly suitable in this study. This should be the focus for future research, as a validation is of utmost importance.

A possible overrepresentation of vegetation-parameters is indicated in this study. To decrease the number of vegetation parameters, it would be necessary to study the correlation between the different vegetation parameters and *Cx. pipiens* prevalence. LAI is a strong indicator for many different ecosystem services, as discussed previously, and is a well-studied vegetation parameter. To find a correlation between LAI and *Cx. pipiens* prevalence would be highly interesting, as such a correlation would significantly improve models like the one presented here.

Furthermore, a continued development of these models should attempt to combine the WMCA-part and the Graphical Modeler. It was a tedious task to go back and forth between the two in this study. Similar studies in the future should try to merge the two steps, for a smoother workflow and easier reproducibility.

7. Conclusion

In conclusion, this study has produced models that simulate the suitability for oviposition sites and adult distribution for the *Cx. pipiens* on a city scale, using the city of Gothenburg as a case study. The results from both models indicate large intra-urban differences which are well matched with previous research. The highest suitability regarding oviposition sites is found in cemeteries, residential gardens, and allotments. Highest suitability for adult distribution is found in vegetated areas. The sensitivity analysis indicates that the modelled suitability is affected by altered parameter weights. The main take away from the sensitivity analysis is that the vegetation parameters perhaps are overrepresented, as they make up a high weight relative to other parameters. The exposure analysis indicates that human exposure to *Cx. pipiens* in Gothenburg is relatively low. However, previous research claims that a warming, and potentially more drought prone climate in the future might change mosquito-human interactions. Previous studies have shown that invasive species may establish themselves in new areas as temperatures rise. Additionally, higher temperatures will increase the survivability for pathogens and viruses in both *Cx. pipiens* and other mosquitoes. Models like the ones produced in this study are of high importance, as they can improve surveillance and mitigation measures of native, and invasive, disease-carrying species of mosquitoes.

Lastly, this study shows that it is possible to utilize WMCA to model mosquito suitability in an urban environment, but further research is needed. Future research should focus on validating the models produced here, by doing a sample study of egg, larvae and adult *Cx. pipiens* in areas with highest suitability in the model simulations. Further studies are also needed to further develop the models, both regarding parameter choices and technical solutions.

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Appendix 1. Reclassified values, oviposition model.

Reclassified values in the oviposition-model for the NMD land cover-data.

Reclassified value oviposition model	Land cover(s)
0	Artificial surfaces, road/railway. Lakes or water-courses Sea, ocean, estuaries or coastal lagoons
1	Artificial surfaces, buildings
2	Non-vegetated other open land
3	Artificial surfaces, not buildings or road/railway
4	Arable land Vegetated other open land Pine forest not on wetland Spruce forest not on wetland Mixed coniferous not on wetland Temporarily non-forest not on wetland Flat roofs
5	Mixed forest not on wetland Deciduous forest not on wetland
6	Deciduous hardwood forest not on wetland Deciduous forest with deciduous hardwood forest not on wetland Pine forest on wetland Spruce forest on wetland Mixed coniferous on wetland Temporarily non-forest on wetland
7	Open wetland Mixed forest on wetland Deciduous forest on wetland
8	Deciduous forest with deciduous hardwood forest on wetland
9	Deciduous hardwood forest on wetland
10	-

Reclassified values in the oviposition-model for the NMD land use-data.

Reclassified value oviposition model	Land use(s)
0	-
1	-
2	Airport Motor racing track
3	All areas without specific land use Sports and training facility
4	Peat extraction site
5	Mining area Grazing area Power lines Ski slope Industrial area
6	Quarries Golf course Waste or recycling facility
7	Camping site
8	-
9	Cemeteries Allotment gardens Residential gardens
10	-

Reclassified values in the oviposition-model for the Intra Urban Heat Difference (IUHD)-data.

Reclassified value oviposition model	IUHD value (°C)
0	-
1	-3 – -2.33
2	-2.33 – -1.66
3	-1.66 – -0.99
4	-0.99 – -0.33
5	-0.33 – 0.33

6	0.33 – 1
7	1 – 1.66
8	1.66 – 2.33
9	2.33 – 3
10	>=3

Appendix 2. Reclassified values, adult model

Reclassified values in the adult distribution-model for the heatmap-data.

Reclassified value adult model - Heatmap	Heatmap value
0	-
1	0 – 200
2	200 - 400
3	400 – 600
4	600 – 800
5	800 – 1000
6	1000 – 1200
7	1200 – 1400
8	1400 – 1600
9	1600 – 1800
10	> 1800

Reclassified values in the adult distribution-model for the vector land use-data.

Reclassified value adult model – Land use	Land use(s)
0	Water
1	Densely built-up
2	Tall built-up
3	-
4	Open square
5	Low built-up
6	-
7	Open ground Industrial Agricultural (cropland)
8	Agricultural (fruit)

	Coniferous forest
9	Deciduous forest
10	-

Reclassified values in the adult distribution-model for the vegetation height-data.

Reclassified value adult model – Vegetation heights	**Vegetation heights (m)**
0	-
1	-
2	-
3	-
4	-
5	-
6	50 – 30
7	30 – 20
8	20 – 10
9	10 – 5
10	0.5 – 5

Reclassified values in the adult distribution-model for the NMD Land cover-data.

Reclassified value adult model – NMD Land Cover	**Land cover(s)**
0	Artificial surfaces, building Artificial surfaces, not building or road/railway. Artificial surfaces, not building or road/railway. Inland water Marine water
1	-
2	-
3	Non-vegetated other open land

4	Arable land
5	Vegetated other open land. Temporarily non-forest not on wetland
6	Open wetland Temporarily non-forest on wetland
7	Pine forest not on wetland Spruce forest not on wetland Mixed coniferous not on wetland Mixed forest not on wetland
8	Deciduous forest not on wetland Deciduous hardwood forest not on wetland Deciduous forest with deciduous hardwood forest not on wetland Pine forest on wetland Spruce forest on wetland Mixed coniferous on wetland Mixed forest on wetland
9	-
10	Deciduous forest on wetland Deciduous hardwood forest on wetland Deciduous forest with deciduous hardwood forest on wetland

Reclassified values in the adult distribution-model for the Wind reduction by distance from ocean-data.

Reclassified value adult model – Wind reduction by distance from ocean	**Wind speed (m/s)**
0	-
1	2.51 – 2.6
2	2.43 – 2.51
3	2.34 – 2.43
4	2.25 – 2.34
5	2.17 – 2.25
6	2.08 – 2.17
7	1.99 – 2.08

8	1.91 – 1.99
9	1.82 – 1.91
10	1.73 – 1.82

Reclassified values in the adult distribution-model for the Wind patterns by altitude-data.

Reclassified value adult model – Wind patterns, altitude	**Wind speed (m/s)**
0	-
1	5.72 – 6.23
2	5.21 – 5.72
3	4.70 – 5.21
4	4.19 – 4.70
5	3.69 – 4.19
6	3.18 – 3.69
7	2.67 – 3.18
8	2.16 – 2.37
9	1.65 – 2.16
10	1.14 – 1.65

Reclassified values in the adult distribution-model for the λp_{veg} -data.

Reclassified value adult model – λp_{veg}	**λp_{veg}**
0	-
1	0 – 0.1
2	0.1 – 0.2
3	0.2 – 0.3
4	0.3 – 0.4
5	0.4 – 0.5
6	0.5 – 0.6
7	0.6 – 0.7
8	0.7 – 0.8
9	0.8 – 0.9
10	0.9 - 1

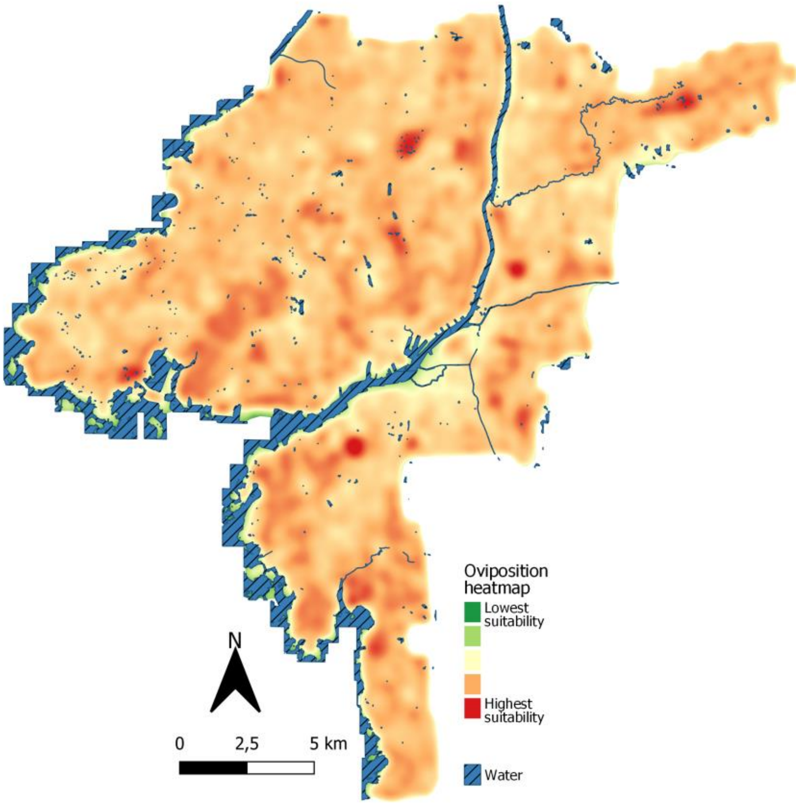
Reclassified values in the adult distribution-model for the Merged LAI, λ_{Fveg} and $\lambda_{Fbuildings}$ -data.

Reclassified value adult model – Merged LAI, λ_{Fveg} and $\lambda_{Fbuildings}$	Merged LAI, λ_{Fveg} and $\lambda_{Fbuildings}$
0	-
1	0 – 0.05
2	-
3	-
4	0.05 – 0.5
5	0.1 – 1
6	1 – 1.5
7	1.5 – 2
8	2 – 2.5
9	2.5 – 3
10	>3

Reclassified values in the adult distribution-model for the LAI -data.

Reclassified value adult model – LAI	LAI
0	-
1	0 – 0.05
2	-
3	-
4	0.05 – 0.5
5	0.1 – 1
6	1 – 1.5
7	1.5 – 2
8	2 – 2.5
9	2.5 – 3
10	>3

Appendix 3. Heatmap



A map showing the heatmap produced in the heatmap model.